Application of Vector Autoregression and Synthetic Control Methods to the Chinese Exchange Traded Funds Market

by

Binwei CHEN

A thesis presented for the degree of
Doctor of Philosophy

University of East Anglia
School of Economics

January 2022

Abstract

This thesis presents three empirical studies on the burgeoning Chinese ETFs market. The first study shows that the frequently used reverse repurchase agreement (repo) by the Chinese central bank from January 2016 to December 2018 has an insignificant impact on ETFs mispricing level on average. The subsequent two studies apply the synthetic control method and compare results with the Difference-in-Differences method (DiD). The second research shows that ETFs with margin trading and short selling qualification improve trading volume significantly. The final study finds that the ETFs options introductions positively influence the liquidity and efficiency of treated ETFs.

Acknowledgements

I express deep gratitude to my supervisor Alasdair Brown. All the guidance and kindness I received inspired me to become a better person who can help and warm others like him. His professional knowledge and excellent academic supervision let me finish my PhD very efficiently during the coronavirus—19 pandemic.

I am particularly grateful to my second supervisor Fuyu Yang. Not only she provides great suggestions to my academic writing, but also her meticulous working attitude inspires all of her students.

I do appreciate the Funds for Women Graduates (FfWG) provided financial support and helped me to complete my PhD in the final stage.

I dedicate this thesis to my respectable and unselfish grandparents and parents.

Life is hard sometimes, but I am lucky to have all of you on my side.

Contents

List of Figures

List of Tables

List of Abbreviations

ARCH Autoregressive Conditional Heteroskedasticity

ATT Average Treatment Effect

CSMAR China Stock Market and Accounting Research Database

CSRC China Securities Regulatory Commission

DiD Difference-in-Differences

ETFs Exchange Traded Funds

FEct Fixed-effect Counterfactual Estimator

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GSC Generalized Synthetic Control

IFEct Interactive Fixed-effect Counterfactual Estimator

MC Matrix Completion

MLF Medium-term Lending Facility

MS-VAR Markov Switching Vector Autoregression

MSPE Mean Squared Prediction Error

NAV Net Asset Value

PSM Propensity Score Matching

repo Repurchase Agreement

RESSET Research Set

S-ARCH Spatial Autoregressive Conditional Heteroskedasticity

S-GARCH Spatial Generalized Autoregressive Conditional Heteroskedasticity

SLF Standing Lending Facility

SLO Short-term Liquidity Operations

SVAR Structural Vector Autoregression

SVD Singular Value Decomposition

TAR Threshold Autoregression

TMLF Targeted Medium-term Lending Facility

VAR Vector Autoregression

VMA Vector Moving Average

Chapter 1

Introduction

The Exchange Traded Funds (ETFs) track the performance of a basket of underlying securities—stocks, bonds, commodities and other tradable securities in the market. In the Chinese market, the total market value of ETFs has been grown tremendously since 2015, which indicates the increasing attention and demand of investors. Enormous studies compare the market performance between ETFs and traditional mutual funds or evaluate the impact of ETFs trading on their underlying securities (Ackert and Tian, 2008; Agapova, 2011; Gastineau, 2004; Poterba and Shoven, 2002), while a few papers pay attention to the influence of recent financial events on the ETF market. This thesis intends to extend the literature in the fields of three hot spots in the Chinese market.

The Chinese central bank has been using reverse repo frequently to adjust market liquidity since 2012. Current monetary policy has become more focused on the central bank balance sheets rather than price setting, which generally expands by assets purchasing (Joyce et al., 2012). The theoretical model of García-Cicco and Kawamura (2014) considers unconventional monetary policy where banks acquire liquidity from outright purchase and repo. Different from the conventional monetary theory that money transactions quantities would be irrelevant (Woodford and Walsh, 2005), their model (García-Cicco and Kawamura, 2014) describes an expansion effect on the economy when the central bank accepts additional collateral for extra liquidity. Researchers (Wang, Tsai and Lu, 2019) have discussed market reactions towards a variety of new monetary policy tools, but have not explored whether repo operations have an impact on financial markets. Do central bank purchases matter in the financial market? I begin my study by investigating whether reverse repo impacts the mispricing level of Chinese ETFs.

Further, I focus on two microeconomics events in the ETF market. Chapter 3 studies the impact of margin trading and short selling qualification on the treated ETFs, and chapter 4 discusses the causal effect of ETFs options introductions. The main contribution of chapter 3 and chapter 4 is the successful application of synthetic control methods on financial market design. Synthetic control methods are arguably regarded as the most essential innovation in policy evaluation literature over the last 15 years (Athey and Imbens, 2017), which is initially introduced by Abadie and Gardeazabal (2003). Previously, economists usually investigated the effect of a policy or event by traditional policy evaluation methods such as comparative case studying, DiD method, and propensity score matching.

Researchers need to construct counterfactuals where the policy or event has not been implemented in Rubin's counterfactual framework. A common solution is to find an appropriate control group —an untreated unit similar to the treated unit, as a counterfactual for the treated unit. But it is ambiguous to find matched control group properly. Synthetic control methods establish an optimal control group by assigning different weights to several control units, which reduce the error of subjective choice. Chapter 5 discusses the limitations of applying synthetic control methods and proposes an idea to generate high-frequent volatility counterfactuals for future financial research.

Chapter 2

Reverse Repo and ETFs Mispricing—Based on SVAR Model

Abstract

This study examines the impact of reverse repo on the average ETFs mispricing level in the Chinese market. I apply the Structural Vector Autoregression (SVAR) model and find that reverse repo has an insignificant impact on ETFs mispricing level from January 2016 to December 2018. ETFs mispricing level increases immediately after its mispricing shock and slowly declines to a certain mispricing level, which implies a persistent mispricing phenomenon in the Chinese ETFs market. The estimated results show that the Chinese central bank reduces the amount of reverse repo in response to its own reverse repo shock.

2.1 Introduction

ETFs are financial innovation products, which consist of a bundle of stocks and are usually designed to mimic a specific index. The creation and redemption process is a unique mechanism for ETFs, which separates ETFs from mutual funds. The process allows authorized participants to change baskets of shares with the same composition at any time for ETFs with the funds and vice versa. As the value of the ETFs is based on the weighted average of each benchmark's net asset value (NAV), arbitrageurs can acquire profits by eliminating the difference between NAV and the secondary market price. Consequently, arbitrage activities enable these two prices to be close to each other. A variety of studies discuss ETFs tracking ability and mispricing reasons from the aspect of ETFs itself or stock market volatility. This chapter firstly investigates whether the short-term liquidity released by reverse repo has an impact on ETFs mispricing level from January 2016 to December 2018.

Economists explain ETFs mispricing from different aspects. Kreis and Licht (2018) document a profitable long-short trading strategy exploiting deviations between ETFs market prices and benchmark index prices, which highlights the transaction costs impact on arbitrage activity. Blitz et al. (2012) find European ETFs underperform their benchmark indexes around 50 to 150 basis points per year. Their results indicate that not only fund expenses but also dividend taxation can lead to a substantial drag on the performance of ETFs. The choice of replication strategy also affects ETFs tracking ability. Generally, ETFs adopt a non-replication strategy that has higher tracking errors than full replication ETFs' tracking errors (Canakgoz and Beasley, 2009); ETFs adopt optimal replication strategy have lower transaction costs since changes in the index composition do not require to trade all constitute securities. Chen et al. (2016) extend ETFs price efficiency discussion by investigating ETFs active management. Specifically, traditional passively-managed ETFs are associated with lower price efficiency and more deviation from a random walk. Also, they document that contrarian and momentum strategies have significant profits in passively managed ETFs, while no significant result for actively managed ETFs. Different trading hours also influence ETFs price efficiency because NAV calculation time differs from domestic ETFs market closing times. Engle and Sarkar (2006) examine ETFs on international indices and find that the average price deviations is 0.35 percent, and price deviations persist around seven days, while the average price deviations of domestic ETFs is 0.01 percent and price deviations only continue several minutes. Levy and Lieberman (2013) compare 17 international ETFs during overlapping trading hours and non-overlapping trading hours. They find that the US market returns have the most considerable influence on these 17 ETFs returns after foreign market closing and the NAV returns account for a more substantial part of ETFs returns during the overlapping hours.

In recent years, the Chinese central bank has been using single reverse repo frequently to inject liquidity,[1] but it does not signify a quantitative easing policy. Firstly, multiple instruments are used to achieve different targets and no standard instrument can be used solely as monetary policy indicator (Chen et al., 2017; Sun, 2013). Secondly, the 7-day interbank pledge repo rate and the one-year benchmark deposit rate is far greater than zero, which means policy rates have adjustment space for the Chinese central bank. Thirdly, reverse repo does not increase the monetary base because they offset automatically on maturity dates. Fourthly, the Chinese central bank tries to use reverse repo and cooperates with the Standing Lending Facility (SLF), Medium-term Lending Facility (MLF), Targeted Medium-term Lending Facility (TMLF), and other directional monetary policy tools to stable market. More accurately, reverse repo is regarded as an important tool for the Chinese central bank to manage macroeconomic regulations and build the 'interest rate corridor' (Kim and Chen, 2019).[2] Another extra short term liquidity adjustment tool—— Short-term Liquidity Operations (SLO) is a supplement of reverse repo, which also has a significant impact on Chinese benchmark interest rate and market expectations (Wang, Tsai and Chen, 2019).

A large area of literature investigates the influence of innovation and traditional monetary instruments on financial markets. There are early theoretical literature about monetary policy and stock market (Blanchard, 1981; Lucas et al., 2012; Svensson, 1986). A series of theoretical models support the connection between funding liquidity and market liquidity. Brunnermeier and Pedersen (2009) show that funding liquidity and market liquidity can reinforce each other, and that the effect of speculator capital on market liquidity is highly nonlinear. The repo market is important in monetary policy and the liquidity transmission process through

[1] Other open market operations used by the Chinese central bank include Treasury deposits, repo and central bank bills (Qiao and Liu, 2017).

[2] The Chinese central bank chooses the pledged 7-day interbank repo rate DR007 as the short-term policy target rate, which is highly related with the 7-day repo rate R007. In 2015, Chinese central bank proposed to use 7-day SLF (Standing Lending Facility) as the upper limit of the interest rate corridor. The interest rate on excess reserves is the lower limit of the interest rate corridor (Kim and Chen, 2019).

the financial system, but the implementation effect is not always clear. From the empirical aspect, Klee and Stebunovs (2011) argue that the federal funds rate has deteriorated after the financial crisis, and the treasury general collateral repo rate might be a better monetary policy tool due to broader market participants. Wang, Tsai and Lu (2019) investigate the Chinese money policy transmission from money market to stock market and bond market, suggesting that novel monetary policy tools such as SLO, MLF, and PSL have positive impact on market regulation. Chen et al. (2017) find that easing monetary conditions raise stock prices but a tight monetary shock shows no significant effect on stock prices. However, researchers have not explored whether the recently frequently used reverse repo in China has an impact on financial markets. This chapter enriches the literature from a new perspective—whether reverse repo implements reduce the average mispricing level of Chinese ETFs.

The following section introduces the research background and presents data. The methodology section 2.3 presents the SVAR model. The results section 2.4 reports model estimates and impulse response analysis. The final section 2.5 provides a summary of the research findings.

2.2 Background

2.2.1 Chinese ETFs Market

The Chinese market launched the first ETF product—Shanghai 50ETF in December 2004. In Figure 2.1, the total ETFs market value excesses 6,500 billion yuan in November of 2019. The total number of ETFs is more than 220, which is nearly tripled compared with the number in 2012.

An essential component of ETFs mispricing can arise from the arbitrage limitation. ETFs arbitrage process includes creation and redemption and covers the primary market and the secondary market. The creation requires a basket of underlying securities or some cash substitution (usually less than 50 percent) to change ETFs shares. The redemption means using ETFs shares to switch a basket of underlying

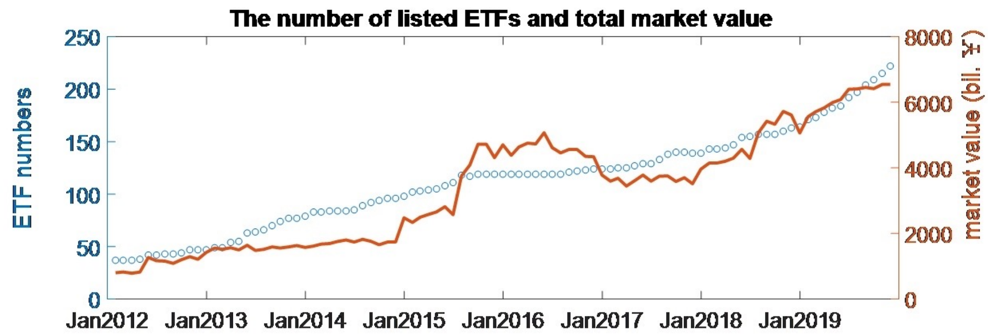


Figure 2.1: The number of listed ETFs and the total market value

securities. The transaction agencies are the main arbitragers, since one unit of ETFs in-kind creation and redemption refers to minimum 1,000,000 shares. The creation and redemption prices of ETFs rely on the net asset value, while ETFs market price bases on a supply and demand relationship in the secondary market. Theoretically, if ETFs market price does not equal ETFs net asset value, investors should repeat arbitrage operations until the ETF's market price equals its net asset value (NAV).

From the perspective of ETFs mispricing, arbitrage activities can be classified as two types: 1) arbitrage bases on realized price differences between market price and its net asset value and 2) arbitrage bases on predicted price differences between ETFs market price and its net asset value. Figure 2.2 and Figure 2.3 display these two arbitrage processes, respectively. If an ETF's market price in the secondary market excesses its net asset value in the primary market, arbitragers can benefit from the ETF's premium by buying a basket of the ETF's underlying securities with relatively low prices then selling newly created ETFs shares in the secondary market with higher prices. If an ETF's market price in the secondary market is lower than its net asset value in the primary market, arbitragers can also earn profits from the ETF's discounts by buying ETFs shares in the secondary market with relatively low prices and redeem a basket of underlying securities in the primary market. Arbitragers come back to the secondary market to sell these underlying securities with higher prices. Usually, ETFs have a certain degree of premium or discount due to arbitrage limitation, such as transaction costs, market interest rates, market liquidity, and some underlying securities' temporary suspension.

However, ETFs arbitrage is not necessarily based on the realized price difference between ETFs market price and its net asset value. If a constituent stock has temporary suspension due to share reform, share allotment or other reasons, investors can also have discount or premium arbitrage activities by predicting whether the constituent security has extreme price rises or falls after the market opened up again. For example, if the constituent stock has high possibilities of significant price growth, investors will do discount arbitrage by purchasing the suspended stock via ETFs, which have this constituent stock. Then, investors redeem ETFs in the primary market and exchange a basket of underlying securities, which include the suspended stock. Next, investors sell underlying securities except for the suspended stock. After repeating previous steps, investors acquire a lot of suspending stock shares by ETFs redemption. In the end, arbitragers sell these stock shares in the secondary with much higher prices when the suspended stock resumes trading. If the constituent stock has critical bad news during its suspension time, investors can short this stock by ETFs creation process. Specifically, investors can take advantage of the cash substitute rule and use cash to replace the suspended stock. Then, investors create new ETFs shares in the primary market by a basket of underlying securities plus cash and sell ETF shares in the secondary market. In this case, arbitrage profits come from the difference between cash substitute price during the suspension period and market price on the day on resumption.

2.2.2 Repo and Short Term Liquidity Operations

Repo is regarded as one of the critical open market operations, which refers to affect the supply of reverse balances in the banking system via trading marketable securities and thereby influence interest rates and money supply. Specifically, a sell repo is a short-term liquidity withdrawal tool coupled with an agreement to repurchase securities on a negotiated date. A reverse repo is used by the central bank to release temporary liquidity. For example, the Chinese central bank purchases securities from primary dealers and promising to resell the same securities back later. Repo has a built-in function to rebalance liquidity. If the central bank uses sell repo or reverse repo to withdraw or input liquidity without renewal, expired sell repo or expired reverse repo will input or withdrawal the same capital as the opposite direction of

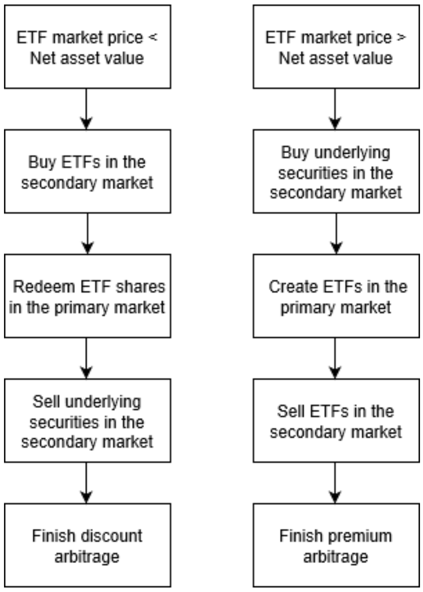


Figure 2.2: Arbitrage type 1

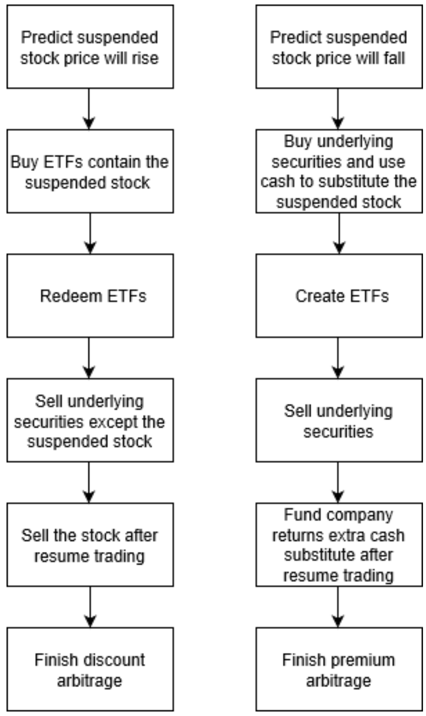


Figure 2.3: Arbitrage type 2

previous repo operations. Adrian and Shin (2008) state that the development of repo size is associated with monetary policy easing. The market liquidity increases and the monetary policy is loose when the repo grows. In contrast, market liquidity declines when monetary policy is tight and the speed of repo growth slows down. Gorton and Metrick (2012) highlight the importance of repo during financial crisis in 2007 and 2008. They argue that repo is the main funding source of scrutinized banking and a run in repo led to liquidity fear which would dry up for collateral. The expected rise in volatility caused repo haircuts to increase, which equates to significant withdrawals from the banking system.

Figure 2.4 shows issued repo, excluding naturally expired repo from January 2002 to June 2019. Generally, repo can be differentiated into three periods: a sell repo period lasting from 2002 to 2011 solely to withdraw extra liquidity frequently; an adjustment phase from 2012 to 2014 with sell repo and reverse repo combination; and a pure reverse repo from 2015 until 2019. The first turning point in the Chinese repo market occurs in 2012. The central bank takes reverse repo operation intensively and ends four years no reverse repurchases operation record. In 2013, China experienced economic stagnation and the "money shortage" outbreaks in June. Accordingly, Figure 2.4 shows that repo interest rates are higher than historical records.

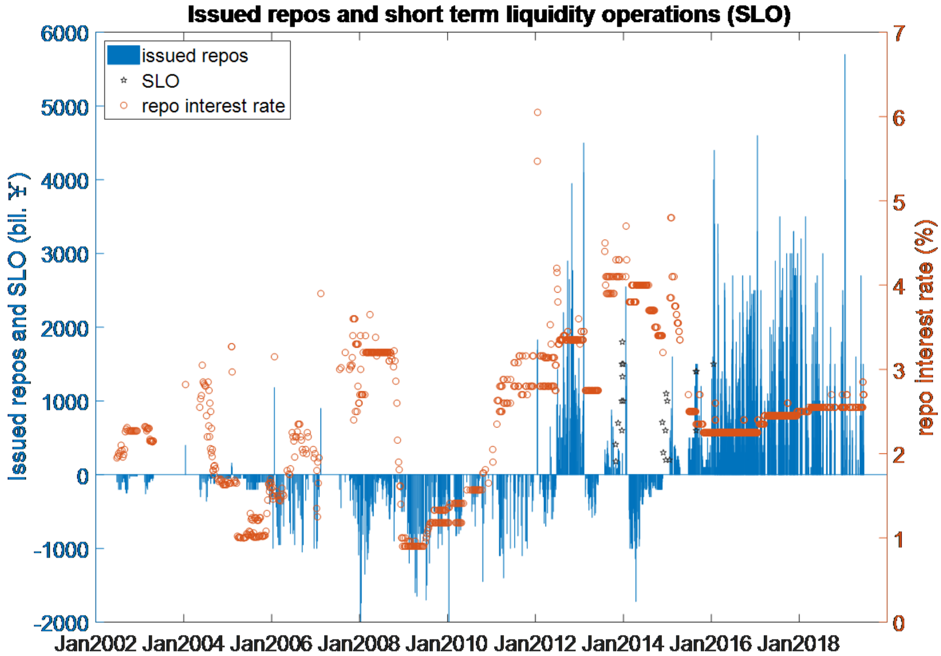


Figure 2.4: Issued repos and SLO

Since July 2013, the central bank has not issued a new central bank bill, while repo and SLO have become more frequent. Figure 2.4 shows that SLO only appears between 2013 and 2016 corporate with repo to smooth short term liquidity fluctuations. Essentially, it is a type of additional short term reverse repo, which is usually expired within one week. Similar to reverse repo, SLO has primary dealers as counterparts. But SLO disclosures information after one month thus, its expectation effect should be minimal. Later, the Chinese central bank adopts short term and medium-term liquidity innovations such as Temporary Lending Facility (TLF), Standing Lending Facility (SLF), Medium-term Lending Facility (MLF) and Pledged Supplement Lending (PSL).

The Chinese central bank declines reserve deposit rate eight times and executes a whole year reverse repurchase 77 times in 2015.[3] In 2016, as the frequency of reverse repo operations grows around 4.8 times and reverse repo size expanses 7.7 times compared with last year. In 2017, under the background of de-leveraging domestic financial policy, the central bank continued high frequency of reverse repo. In 2018, the reverse repo still plays an important role in open market operations, but the frequency and total amount of repo shrink more than half-size compared with the

[3]China Bond Annual Report, 2007-2011

previous year.

2.3 Methodology

2.3.1 The Standard VAR Method

Sims (1980) first introduces the vector autoregression model (VAR) into economic research. Monetary policies have multiple transmission paths and often along with time-lag effect, and VAR model is one of the commonly used methods to describe monetary policy implementation effects.

I denote vectors in lower-case bold, matrices in upper-case bold, variables and coefficients in general lower-case. The general unrestricted VAR(k, p) model without exogenous variable can be written as:

$$\boldsymbol{y}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \boldsymbol{A}_2 \boldsymbol{y}_{t-2} + \cdots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon_t},\ t = 1, ..., T, \tag{2.1}$$

or

$$\boldsymbol{A}(L)\boldsymbol{y}_t = \boldsymbol{\varepsilon_t},\ t = 1, ..., T, \tag{2.2}$$

where $\boldsymbol{y_t}$ is a k dimension column vector, p is the lag order, L is the lag operator such that $L^i \boldsymbol{y}_t = \boldsymbol{y}_{t-i},\ i = \cdots, -1, 0, 1, 2, \cdots,$ $\boldsymbol{A}(L)$ is a $k \times k$ dimension matrix of lag operator L which is under estimation, $\boldsymbol{\varepsilon_t}$ is a k dimension column error vector with $\boldsymbol{\varepsilon_t} \sim iid(0, \boldsymbol{\Sigma}_\varepsilon)$, and $\boldsymbol{\Sigma}_\varepsilon$ is the $k \times k$ covariance matrix.

Expanding equation 2.1 gives

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{kt} \end{pmatrix} = \boldsymbol{A}_1 \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ \vdots \\ y_{kt-1} \end{pmatrix} + \boldsymbol{A}_2 \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \\ \vdots \\ y_{kt-2} \end{pmatrix} + \cdots + \boldsymbol{A}_p \begin{pmatrix} y_{1t-p} \\ y_{2t-p} \\ \vdots \\ y_{kt-p} \end{pmatrix}, \tag{2.3}$$

Expanding equation 2.2 gives

$$(\boldsymbol{A}_0 - \boldsymbol{A}_1 L - \boldsymbol{A}_2 L^2 - \cdots - \boldsymbol{A}_p L^p)\boldsymbol{y}_t = \boldsymbol{\varepsilon_t}, \tag{2.4}$$

where $A_0 = I_k$ ($k \times k$ unit matrix).

The dynamic properties of the VAR model can be investigated by calculating the roots of the characteristic function or the roots of the companion matrix.

The characteristic polynomial is

$$\boldsymbol{A}(L) = \boldsymbol{I}_k - \boldsymbol{A}_1 L - \boldsymbol{A}_2 L^2 - \cdots - \boldsymbol{A}_p L^p \tag{2.5}$$

If $\det[\boldsymbol{A}(L)]$ roots are outside the unit circle, the VAR model is stationary. We assume $\boldsymbol{A}(L)$ is invertible, then equation 2.2 can be expressed as:

$$\boldsymbol{y}_t = \boldsymbol{B}(L)\boldsymbol{\varepsilon_t}, \tag{2.6}$$

where $\boldsymbol{B}(L) = \boldsymbol{A}(L)^{-1}$, $\boldsymbol{B}(L) = \boldsymbol{B}_0 + \boldsymbol{B}_1 L + \boldsymbol{B}_2 L^2 + \cdots, \boldsymbol{B}_0 = \boldsymbol{I}_k$.

By transforming the VAR(k, p) model[4], we can have the companion form of the characteristic function:

$$\begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-k+1} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A}_1 & \boldsymbol{A}_2 & \cdots & \boldsymbol{A}_{k-1} & \boldsymbol{A}_k \\ I & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-k} \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \varepsilon_{t-1} \\ \vdots \\ \varepsilon_{t-k+1} \end{pmatrix} \tag{2.7}$$

or more compactly

$$\boldsymbol{\tilde{y}_t} = \boldsymbol{\tilde{A}}\boldsymbol{\tilde{y}_{t-1}} + \boldsymbol{\tilde{\varepsilon}_t}, \ t = 1, ..., T, \tag{2.8}$$

where $\boldsymbol{\tilde{A}}$ is the $k \times k$ companion matrix. If the roots of $\boldsymbol{\tilde{A}}$ are inside the unit circle, the VAR model is stationary.

2.3.2 A Simple Two-Variable Structural VAR Model

Equation 2.1 to 2.3 do not show the contemporaneous relationships among variables, while the structual VAR model (SVAR) discusses the contemporaneous causality between variables. Following Enders (2014), we shall firstly consider a simple bivariate

[4]Johansen et al. (1995) illustrate details in 'Likelihood-based Inference in Cointegrated Vector Autoregressive Models', Chapter 2.

system:

$$\begin{cases} y_{1t} = -c_{12}y_{2t} + \gamma_{11}y_{1t-1} + \gamma_{12}y_{2t-1} + s_{1t} \\ y_{2t} = -c_{21}y_{1t} + \gamma_{21}y_{2t-1} + \gamma_{22}y_{2t-1} + s_{2t} \end{cases}, \ t = 1, ..., T, \tag{2.9}$$

where y_{1t} and y_{2t} are stationary, y_{1t} is affected by current and past realizations of y_{2t}, and y_{2t} are affected by current and past realizations of y_{1t}; s_{1t} and s_{2t} are white-noise disturbances with standard deviations and s_{1t} and s_{2t} are uncorrelated. Here we assume $E(s_{1t}^2) = E(s_{2t}^2) = 1$. c_{12} is the contemporaneous effects of a unit change of y_{2t} on y_{1t}, and γ_{12} is the effect of a unit change in y_{2t-1} on y_{1t}. s_{1t} and s_{2t} are shocks in y_{1t} and y_{2t}, respectively. If $c_{21} \neq 0$, s_{1t} has an indirect contemporaneous effect on y_{2t}. If $c_{12} \neq 0$, s_{2t} has an indirect contemporaneous effect on y_{1t}. Therefore, we cannot use OLS to estimate equation 2.9 because y_{1t} and y_{2t} are contemporaneously related.

We can rewrite equation 2.9 as a matrix form:

$$\boldsymbol{C}\boldsymbol{y_t} = \boldsymbol{\Gamma_1}\boldsymbol{y_{t-1}} + \boldsymbol{s_t}, \ t = 1, ..., T, \tag{2.10}$$

where

$$\boldsymbol{C} = \begin{pmatrix} 1 & c_{12} \\ c_{21} & 1 \end{pmatrix}, \boldsymbol{y_t} = \begin{pmatrix} y_{11} \\ y_{21} \end{pmatrix}, \boldsymbol{\Gamma_1} = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix}, \boldsymbol{s_t} = \begin{pmatrix} s_{11} \\ s_{21} \end{pmatrix},$$

and assume $\boldsymbol{s}_t \sim iid(\boldsymbol{0}, \boldsymbol{\Sigma_s})$. Assume $\boldsymbol{C}$ is invertible, we multiply $\boldsymbol{C}^{-1}$ in both sides of equation 2.10 and we can get the VAR model form:

$$\boldsymbol{y_t} = \boldsymbol{C}^{-1}\boldsymbol{\Gamma_1}\boldsymbol{y_{t-1}} + \boldsymbol{C}^{-1}\boldsymbol{s_t} \tag{2.11}$$

Recall the equation 2.2 and write the VAR(2,1):

$$\boldsymbol{y_t} = \boldsymbol{A_1}\boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon_t}. \tag{2.12}$$

we can see that

$$\boldsymbol{A_1} = \boldsymbol{C}^{-1}\boldsymbol{\Gamma_1}, \quad \boldsymbol{\varepsilon_t} = \boldsymbol{C}^{-1}\boldsymbol{s_t}.$$

Furthermore, if we expand $\boldsymbol{\varepsilon_t} = \boldsymbol{C^{-1}s}_t$,

$$\begin{aligned}\begin{pmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{pmatrix} &= \begin{pmatrix}1 & c_{12}\\ c_{21} & 1\end{pmatrix}^{-1}\begin{pmatrix}s_{1t}\\ s_{2t}\end{pmatrix}\\ &= \frac{1}{1-c_{12}c_{21}}\begin{pmatrix}1 & -c_{12}\\ -c_{21} & 1\end{pmatrix}\begin{pmatrix}s_{1t}\\ s_{2t}\end{pmatrix}\end{aligned} \tag{2.13}$$

we will see a clear relationship between VAR and SVAR error term:

$$\varepsilon_{1t} = \frac{s_{1t} - c_{12}s_{2t}}{1 - c_{12}c_{21}} \tag{2.14}$$

$$\varepsilon_{2t} = \frac{s_{2t} - c_{21}s_{1t}}{1 - c_{12}c_{21}} \tag{2.15}$$

The contemporaneous covariance between ε_{1t} and ε_{2t} is

$$cov(\varepsilon_{1t}, \varepsilon_{2t}) = E(\varepsilon_{1t}, \varepsilon_{2t}) = \frac{(s_{1t} - c_{12}s_{2t})(s_{2t} - c_{21}s_{1t})}{(1 - c_{12}c_{21})^2} = -\frac{(c_{21}\sigma^2_{s_1} + c_{12}\sigma^2_{s_2})}{(1 - c_{12}c_{21})^2}. \tag{2.16}$$

The variance-covariance matrix is

$$\boldsymbol{\Sigma}_\varepsilon = \begin{pmatrix}var(\varepsilon_{1t}) & cov(\varepsilon_{1t}, \varepsilon_{2t})\\ cov(\varepsilon_{1t}, \varepsilon_{2t}) & var(\varepsilon_{2t})\end{pmatrix} = \begin{pmatrix}\sigma_{11} & \sigma_{12}\\ \sigma_{21} & \sigma_{22}\end{pmatrix} = \begin{pmatrix}\sigma_1^2 & \sigma_{12}\\ \sigma_{21} & \sigma_2^2\end{pmatrix} \tag{2.17}$$

In general, the error term in the reduced VAR model is relevant (If $c_{12} \neq 0$ or $c_{21} \neq 0$, then $cov(s_{1t}, s_{2t}) \neq 0$), which differs from error term in SVAR model (we assumed $cov(\varepsilon_{1t}, \varepsilon_{2t}) = 0$ in equation 2.9). Thus, we need to add restriction on matrix $\boldsymbol{C}$. For example, if we force $c_{21} = 0$ to identify the model, then y_{2t} has a contemporaneous effect on y_{1t}, while y_{1t} influences y_{2t} with one period lag and no contemporaneous effect on y_{2t}. Because both s_{1t} and s_{2t} shocks impact the contemporaneous value on y_{1t}, but only s_{2t} shocks affect the contemporaneous value of y_{2t}. Under the restriction of $c_{21} = 0$, error term in equation 2.14 and 2.16 can be written as:

$$\varepsilon_{1t} = s_{1t} - c_{12}s_{2t} \tag{2.18}$$

and

$$\varepsilon_{2t} = s_{2t}, \tag{2.19}$$

respectively. Ordering variables implies a causal priority, because one shock of s_{2t} directly effects ε_{1t} and ε_{2t}, but a shock of s_{1t} only effects ε_{1t}.

2.3.3 Model Identification

We can write the general SVAR(k,p) model (The A-model):

$$\boldsymbol{C}\boldsymbol{y_t} = \boldsymbol{\Gamma_1}\boldsymbol{y_{t-1}} + \boldsymbol{\Gamma_2}\boldsymbol{y_{t-2}} + \cdots + \boldsymbol{\Gamma_p}\boldsymbol{y_{t-p}} + \boldsymbol{s_t}, \; t = 1, ..., T, \tag{2.20}$$

where $\boldsymbol{C}$ is a $k \times k$ and the diagonal element is 1.

Or

$$\boldsymbol{C}(L)\boldsymbol{y}_t = \boldsymbol{s}_t, \tag{2.21}$$

where $\boldsymbol{C}(L)$ is the $k \times k$ parameter matrix of the lag operator L, $\boldsymbol{C}(L) = \boldsymbol{C}_0 - \boldsymbol{\Gamma_1}\boldsymbol{L} - \boldsymbol{\Gamma_2}\boldsymbol{L^2} - \cdots - \boldsymbol{\Gamma_p}\boldsymbol{L^p}$, $\boldsymbol{C}_0 \neq I_k$ which is different with VAR model (see equation 2.2). We know that $\boldsymbol{\varepsilon_t} = \boldsymbol{C}^{-1}\boldsymbol{s_t}$ and $E(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}) = E[(\boldsymbol{C}^{-1}\boldsymbol{s_t})(\boldsymbol{C}^{-1}\boldsymbol{s_t})']$, then

$$\boldsymbol{\Sigma_\varepsilon} = \boldsymbol{C}^{-1}\boldsymbol{\Sigma}_s\boldsymbol{C}'^{-1} \tag{2.22}$$

If we assume $\boldsymbol{\Sigma}_s$ is an unit matrix, then

$$\boldsymbol{\Sigma_\varepsilon} = \boldsymbol{C}^{-1}\boldsymbol{C}'^{-1} \tag{2.23}$$

For a proper choice of $\boldsymbol{C}$, s_t will have a diagonal covariance matrix and equation 2.22 leads to $k(k-1)/2$ independent equations. The unique model identification requires k^2 unique equations, so we need to find another $k(k+1)/2$ equations by

$$\boldsymbol{R_c} vec(\boldsymbol{C}) = \boldsymbol{r_c}, \tag{2.24}$$

where $\boldsymbol{R_c}$ is a $1/2k(k+1) \times k^2$ dimension selection matrix and r_c is a $1/2k(k+1) \times 1$ vector. Lütkepohl (2005) proves that equation 2.22 and 2.24 can jointly provide local unique identification and achieve a global unique solution if the diagonal elements of matrix $\boldsymbol{C}$ equal to 1. The system of equations 2.22 and 2.24 has a local unique solution only if

$$rk\begin{bmatrix} -2\boldsymbol{S}_k^+(\Sigma_\varepsilon \otimes \boldsymbol{C}^{-1}) & \boldsymbol{S}_k^+(\boldsymbol{C}^{-1} \otimes \boldsymbol{C}^{-1})\boldsymbol{S}_k \\ \boldsymbol{R}_c & 0 \\ 0 & \boldsymbol{R}_\sigma \end{bmatrix} = k^2 + k(k+1)/2. \tag{2.25}$$

Here $\boldsymbol{S}_k$ is a $k^2 \times k(k+1)/2$ dimensional duplication matrix, and $\boldsymbol{S}_k^+$ is its Moore-Penrose inverse $\boldsymbol{S}_k^+ = (\boldsymbol{S}_k'\boldsymbol{S}_k)^{-1}\boldsymbol{S}_k'$. $\boldsymbol{R}_\sigma$ is a $k(k-1)/2 \times k(k+1)/2$ dimensional selection matrix, which selects the elements of $\text{vech}(\Sigma_s)$ below the main diagonal. If $\boldsymbol{\Sigma_s}$ is an unit matrix, we will know its diagonal elements. The unique solution of equations set 2.23 and 2.24 exists only if

$$rk\begin{bmatrix} -2\boldsymbol{S}_k^+(\Sigma_\varepsilon \otimes \boldsymbol{C}^{-1}) \\ \boldsymbol{R}_c \end{bmatrix} = k^2 \tag{2.26}$$

.

The B-model of SVAR is

$$\boldsymbol{y}_t = \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \boldsymbol{A}_2\boldsymbol{y}_{t-2} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{D}\boldsymbol{s_t},\ t = 1, ..., T, \tag{2.27}$$

where we have the relation $\boldsymbol{\varepsilon_t} = \boldsymbol{D}\boldsymbol{s_t}$.

As $E(\boldsymbol{s_t}\boldsymbol{s_t'}) = E[(\boldsymbol{D^{-1}}\varepsilon_t)(\boldsymbol{D^{-1}}\varepsilon_t)'] = \boldsymbol{D}^{-1}E(\varepsilon_t\varepsilon_t')\boldsymbol{D}^{-1'}$, then we have

$$\boldsymbol{\Sigma_s} = \boldsymbol{D}^{-1}\boldsymbol{\Sigma_\varepsilon}\boldsymbol{D}^{-1'}. \tag{2.28}$$

Similarly, the B-model identifications require k^2 unique equations. If we restrict that $\boldsymbol{\Sigma_s}$ is diagonal and $\boldsymbol{\Sigma_\varepsilon}$ is symmetric, we will have $k(k-1)/2$ unique equations. Normalizing the variances of the structural innovations to one $\boldsymbol{\Sigma_s} = \boldsymbol{I_k}$ implies the relationship

$$\boldsymbol{\Sigma_\varepsilon} = \boldsymbol{D}\boldsymbol{D}'. \tag{2.29}$$

The rest of $k(k+1)/2$ unique equations can be obtained by

$$\boldsymbol{R_d} vec(\boldsymbol{D}) = \boldsymbol{r_d}, \tag{2.30}$$

where $\boldsymbol{R_d}$ is a $1/2k(k+1) \times k^2$ dimension selection matrix and $\boldsymbol{r_d}$ is a $1/2k(k+1) \times 1$ vector. Lütkepohl (2005) has proved that there exists an unique solution of equation 2.29 and 2.30 if

$$rk \begin{bmatrix} 2\boldsymbol{S}_k^+(\boldsymbol{D} \otimes \boldsymbol{I}_k) \\ \boldsymbol{R}_d \end{bmatrix} = k^2 \tag{2.31}$$

is satisfied.

The AB-model can be expressed as

$$\boldsymbol{C}\boldsymbol{\varepsilon}_t = \boldsymbol{D}\boldsymbol{s}_t \ t = 1, ..., T, \tag{2.32}$$

where we have $\boldsymbol{\varepsilon}_t = \boldsymbol{C}^{-1}\boldsymbol{D}\boldsymbol{s}_t$ and $\boldsymbol{s}_t \sim iid(\boldsymbol{0}, \boldsymbol{I}_k)$. Then, we can get $k(k+1)/2$ equations from $\boldsymbol{\Sigma_\varepsilon} = \boldsymbol{C}^{-1}\boldsymbol{D}\boldsymbol{D}'\boldsymbol{C}^{-1\prime}$. If we restrict the diagonal elements of $\boldsymbol{C}$ to one, we will get another k equations but still need $2k^2 - k(k+1) - k$ equations to identify all $2k^2$ elements of $\boldsymbol{C}$ and $\boldsymbol{D}$ at least locally. Lütkepohl (2005) has proved that the AB-model can be identified only if

$$\begin{cases} \boldsymbol{\Sigma_\varepsilon} = \boldsymbol{C}^{-1}\boldsymbol{D}\boldsymbol{D}'\boldsymbol{C}^{-1\prime} \\ \boldsymbol{R}_c vec(\boldsymbol{C}) = \boldsymbol{r}_c \\ \boldsymbol{R}_d vec(\boldsymbol{D}) = \boldsymbol{r}_d \end{cases} \tag{2.33}$$

satisfies

$$rk \begin{bmatrix} -2\boldsymbol{S}_k^+(\Sigma_\varepsilon \otimes \boldsymbol{C}^{-1}) & 2\boldsymbol{S}_k^+(\boldsymbol{C}^{-1}\boldsymbol{D} \otimes \boldsymbol{C}^{-1}) \\ \boldsymbol{R}_c & 0 \\ 0 & \boldsymbol{R}_d \end{bmatrix} = 2k^2. \tag{2.34}$$

2.3.4 Impulse Response Function

A popular way to acquire impulse response function is deriving from the VAR process to its moving average representation. The moving average coefficient matrix (VMA) is the impulse response coefficient matrix of the general VAR(p) model (Lütkepohl, 2005). Consider the general stable VAR(p) model in equation 2.1 and its lag operator form in equation 2.2. Let $\mathbf{\Phi}(L) = \sum_{i=0}^{\infty} \mathbf{\Phi}_i L^i$, which satisfies $\mathbf{\Phi}(L)\boldsymbol{A}(L) = \boldsymbol{I}_k$. Multiply $\mathbf{\Phi}(L)$ on both sides of equation 2.2 and get the VMA(∞) representation

$$\mathbf{\Phi}(L)\boldsymbol{A}(L)\boldsymbol{y}_t = \mathbf{\Phi}(L)\boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{y}_t = \mathbf{\Phi}(L)\boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{y}_t = \sum_{i=0}^{\infty} \mathbf{\Phi}_i L^i \boldsymbol{\varepsilon}_t. \tag{2.35}$$

The VAR(p) coefficient matrix and VMA(∞) coefficient matrix must satisfy

$$\begin{aligned}\boldsymbol{I}_k &= (\mathbf{\Phi}_0 + \mathbf{\Phi}_1 L + \mathbf{\Phi}_2 L^2 + ...)(\boldsymbol{I}_k - \boldsymbol{A}_1 L - \boldsymbol{A}_2 L^2 - ... - \boldsymbol{A}_p L^p) \\ &= \mathbf{\Phi}_0 + (\mathbf{\Phi}_1 - \mathbf{\Phi}_0 \boldsymbol{A}_1)L + (\mathbf{\Phi}_2 - \mathbf{\Phi}_1 \boldsymbol{A}_1 - \mathbf{\Phi}_0 \boldsymbol{A}_2)L^2 + ...,\end{aligned}$$

which imply that

$$\boldsymbol{I}_k = \mathbf{\Phi}_0$$

$$0 = \mathbf{\Phi}_1 - \mathbf{\Phi}_0 \boldsymbol{A}_1$$

$$0 = \mathbf{\Phi}_2 - \mathbf{\Phi}_1 \boldsymbol{A}_1 - \mathbf{\Phi}_0 \boldsymbol{A}_2$$

$$\vdots$$

$$0 = \mathbf{\Phi}_i - \sum_{j=1}^{i} \mathbf{\Phi}_{i-j} \boldsymbol{A}_j.$$

We can get the recursive equation for calculating the impulse response coefficient matrix,

$$\mathbf{\Phi}_i = \sum_{j=1}^{i} \mathbf{\Phi}_{i-j} \boldsymbol{A}_j, \tag{2.36}$$

in which $\mathbf{\Phi}_0 = \boldsymbol{I}_k$.

For example, in the two-variable var model

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \phi_{11}^{(0)} & \phi_{12}^{(0)} \\ \phi_{21}^{(0)} & \phi_{22}^{(0)} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(1)} & \phi_{12}^{(1)} \\ \phi_{21}^{(1)} & \phi_{22}^{(1)} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t-1} \\ \varepsilon_{2t-1} \end{pmatrix} + \begin{pmatrix} \phi_{11}^{(2)} & \phi_{12}^{(2)} \\ \phi_{21}^{(2)} & \phi_{22}^{(2)} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t-2} \\ \varepsilon_{2t-2} \end{pmatrix} + ...,$$

if we give one unit shock to y_1 at $t = 0$, the the impulse response function of y_2 is

$$y_{20} = \phi_{21}^{(0)}, t = 0$$

$$y_{21} = \phi_{21}^{(1)}, t = 1$$

$$y_{22} = \phi_{21}^{(2)}, t = 2$$

$$y_{23} = \phi_{21}^{(3)}, t = 3$$

$$y_{24} = \phi_{21}^{(4)}, t = 4$$

$$\vdots$$

$\phi_{jk}^{(i)}$ means that the jk-th element of matrix $\boldsymbol{\Phi}_i$ represents the effect on variable j of a unit innovation in the k-th variable which has occurred i periods ago.

Analogously, we can get the impulse response function of the SVAR AB-model,

$$\boldsymbol{\Phi}_i \boldsymbol{A}^{-1} \boldsymbol{B}, \quad j = 0, 1, 2, ... \tag{2.37}$$

and the correspond accumulated impulse response function is

$$\sum_{i=0}^{n} \boldsymbol{\Phi}_i \boldsymbol{A}^{-1} \boldsymbol{B}, n = 1, 2, ... \tag{2.38}$$

2.3.5 Confidence Intervals

Generally, the coefficient matrix, covariance matrix and impulse responses are unknown in a VAR system, and we need to construct confidence intervals based on their distributions. The residual based bootstrap is commonly applied in this context, which re-samples sample data and creates multiple simulated sample sets without considering the inherent distribution characteristics of the original dataset. For instance, in a stable process with impulse response function, we can build the empirical distribution of impulse response coefficient matrix based on the distribution of the coefficient matrix, and further acquire the confidence bands of the impulse response matrix by bootstrap method.

Lütkepohl (2005) systematically derives the VAR coefficient matrix in the form of a moving average and gives a derivation of the impulse response coefficients asymptotic distribution. Define the function $\boldsymbol{q}_T = \boldsymbol{q}(\boldsymbol{y}_1, ..., \boldsymbol{y}_T)$ of some VAR(p) process, where $\boldsymbol{q}_T$ is an $(M \times 1)$ dimension and represents some estimator or test statistics. In order to investigate the distribution F_T of $\boldsymbol{q}_T$, we firstly assume that a sample $\boldsymbol{y}_1, ..., \boldsymbol{y}_T$ and the required pre-sample values are available. We can get coefficient estimates $\hat{\boldsymbol{v}}, \hat{\boldsymbol{A}}_{\boldsymbol{1}}, ..., \hat{\boldsymbol{A}}_{\boldsymbol{p}}$ and residuals $\hat{\varepsilon}_1, ..., \hat{\varepsilon}_T$ by fitting the model. An estimator of a quantity of interest is obtained $\hat{\boldsymbol{q}} = \boldsymbol{q}(\hat{\boldsymbol{A}}_1, ..., \hat{\boldsymbol{A}}_p)$. Secondly, computing the centred residuals $\hat{\boldsymbol{\varepsilon}}_1 - \bar{\boldsymbol{\varepsilon}}, ..., \hat{\boldsymbol{\varepsilon}}_T - \bar{\boldsymbol{\varepsilon}}$, where $\bar{\boldsymbol{\varepsilon}} = T^{-1} \sum \boldsymbol{\varepsilon}_t$; obtaining bootstrap residuals $\boldsymbol{\varepsilon}_1^*, ..., \boldsymbol{\varepsilon}_T^*$ by randomly replacing the cantered residuals. Thirdly, recursively computing the bootstrap time series $\boldsymbol{y}_t^* = \hat{\boldsymbol{v}} + \hat{\boldsymbol{A}}_{\boldsymbol{1}} \boldsymbol{y}_{t-1}^* + ... + \hat{\boldsymbol{A}}_{\boldsymbol{p}} \boldsymbol{y}_{t-p}^* + \boldsymbol{\varepsilon}_t^*, t = 1, ..., T$. Fourthly, re-estimating the parameters $\boldsymbol{A}_1, ..., \boldsymbol{A}_p$ based on the bootstrap time series $\boldsymbol{y}_t^*$. Fifthly, after applying the estimated parameters from the previous four steps, we can acquire the bootstrapped estimator $\hat{\boldsymbol{q}^*} = \boldsymbol{q}^*(\hat{\boldsymbol{A}}_{\boldsymbol{1}}, ..., \hat{\boldsymbol{A}}_{\boldsymbol{p}})$, where estimator implied in the model coefficients is $\hat{\boldsymbol{q}}$, and its bootstrap estimator is $\hat{\boldsymbol{q}^*}$. Finally, repeating the previous steps N times, where N is large enough.

This chapter uses Stata for bootstrap sampling and estimation, which applies the standard percentile interval (Tibshirani and Efron, 1993) in the content of impulse response analysis. Denoting by $s_{\alpha/2}^*$ and $s_{(1-\alpha/2)}^*$ the $\alpha/2$- and $(1-\alpha/2)$- quantiles respectively for the N bootstrap versions of $\hat{\boldsymbol{q}^*}$, the percentile method yields the confidence intervals

$$CIs = [s_{\alpha/2}^*, s_{(1-\alpha/2)}^*]. \tag{2.39}$$

2.4 Empirical Results

2.4.1 Data and Description

This chapter collects 133 ETFs from RESSET from January 2016 to December 2018. The repo data come from the Chinese central bank official website, which only record reverse repo operations during this sample period. All original data are daily frequency and averaged to weekly frequency for model estimates in the next section.

The widely used measure of ETFs mispricing is defined as the price differential between ETFs market price and its NAV (Jares and Lavin, 2004). This study mainly concerns about the tracking performance response towards the central bank repurchase operations. Thus, the absolute value of price differences would be more suitable than ETFs premium or discount measure. The mispricing variable can be defined as the ETF's market price minus the NAV then divided by the NAV. Another popular way to analyze ETFs tracking performance is calculating the difference between the market price return and its underlying benchmark return (Aber et al., 2009), named tracking deviation or tracking error. This chapter uses the first ETF mispricing measurement and averages all active ETFs' mispricing as the whole ETFs market mispricing.

$$Mispricing_t = \frac{\sum_i^n \frac{|ETF_{it} - NAV_{it}|}{NAV_{it}}}{n_t} \tag{2.40}$$

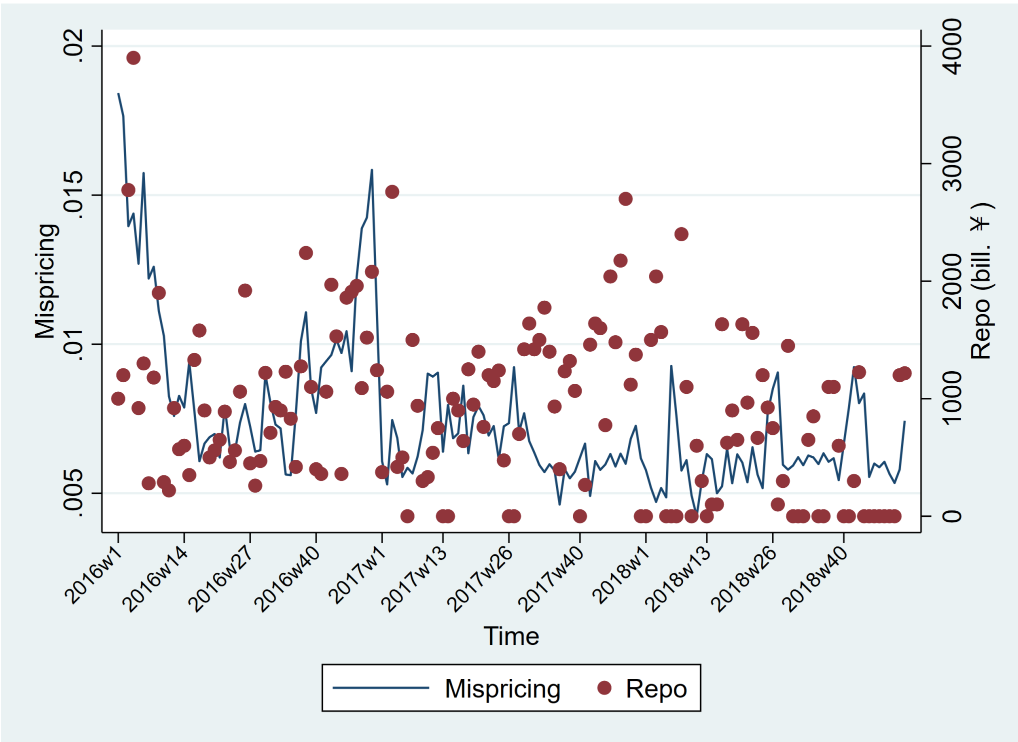


Figure 2.5: Chinese ETFs Market Mispricing and Repo

In Figure 2.5, there are two abnormal ETFs mispricing peaks in 2016 and moderate mispricing peaks in 2018. Accordingly, intensive reverse repo operations occur around the beginning of 2016 and the end of 2016, while less frequent repo operations (replaced by zero value in Figure 2.5) are coordinated with the relative stable mispricing period from 2017 to 2018.

2.4.2 Integration tests

If variables are unstable and variables vary by time, it will cause a spurious regression problem. Thus, it is necessary to test data stationarity before using observed time series to the randomness of the whole sequence. This essay uses ADF test and the results are shown in Table 2.1.

Table 2.1: ADF Test Results

Series	Test statistic	1% Critical value	5% Critical value	10% Critical test	Result
ETF mispricing	-5.116	-3.492	-2.886	-2.576	Stable
Repo	-8.257	-3.492	-2.886	-2.576	Stable

After ensuring time series are stable, it is also important to choose lags properly. The unit root test is very sensitive with lag selection. Generally, a small number of lags leads to unit roots while excessive lags reduce the degree of freedom in a model. In Table 2.2, the optimal selection is 4 according to AIC lag order selection criteria .

Table 2.2: Lag Order Selection Criteria

Lag	LL	LR	FPE	AIC	HQIC	SBIC
1	-398.503	NA	.708511	5.33116	5.36363*	5.41109*
2	-394.625	7.7557	.709674	5.33278	5.39772	5.49264
3	-393.479	2.2916	.737059	5.37058	5.4680	5.61037
4	-383.894	19.17*	.684585*	5.29661*	5.4265	5.61632
5	-381.785	4.218	.702081	5.32166	5.48401	5.7213

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

2.4.3 Model Estimation

The SVAR parameters are obtained from two steps. The first step is obtaining the reduced form VAR in equation 2.1. The lag up to 4 weeks is the optimal length based on the AIC criteria in Table 2.2. The second step is identifying the contemporaneous matrix in equation 2.37.

Table 2.3 reports the model estimates. The whole ETF market's average mispricing level is not influenced by repo operations in this sample. All coefficients of repo are very small and insignificant with the mispricing. Mispricing and repo only have significant positive coefficients with their first lag and fourth lag.

2.4.4 Impulse Response Analysis

The impulse response shows the reaction of a dynamic system after an external change. The x-axis represents lag weeks, and the y-axis represents impulse effects. The solid middle line describes impulse response function, and the upper (lower) grey bound represents two positive (negative) standard errors.

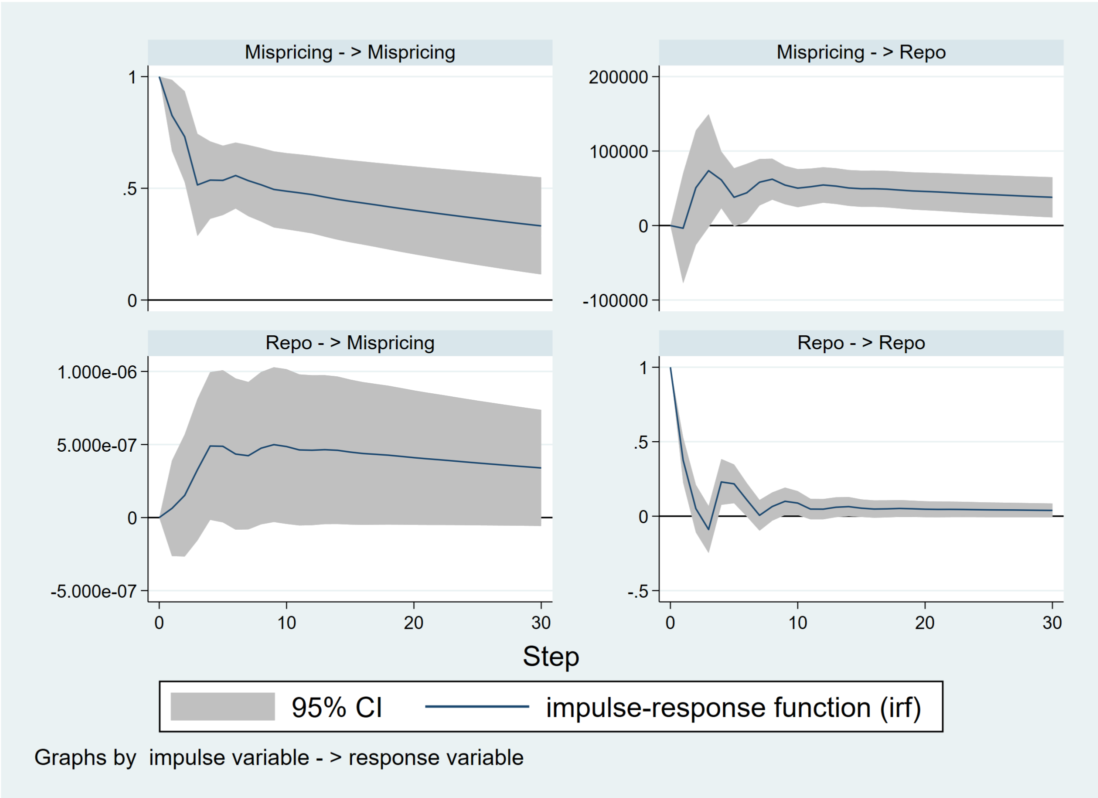


Figure 2.6: Impulse response of SVAR model

Figure 2.6 shows the impulse response of the SVAR model. I select a bootstrap percentile 95 percent confidence interval to illustrate parameter uncertainty and 30 response periods. A one-time positive shock to the average mispricing of ETFs has an positive effect on itself, and the effects decline quickly around the first 4 weeks. The effects are statistically significant. The mispricing level almost has positive but almost negligible and insignificant changes after a unit shock to repo. This provides an important insight into possible capital liquidity demand shocks as a result of the ETF market uncertainty. The graph of the impulse responses of repo shows that a unit shock to the mispricing of ETFs tends to increase the amount of repo operations, while the effects are insignificant. Repo has statistic significant results of its own shock. Repo has a positive response after a unit shock to repo which declines quickly in the first 4 weeks and lasts around 10 weeks before it disappear.

The shock of reverse repo quantities to the mispricing level of Chinese ETFs is weak. There are several possible reasons. Firstly, the Chinese central bank's high frequency of reverse repo during the sample period could not reflect the complete picture of the whole repo market. Fan and Zhang (2007) argue that there are two patterns of repo markets in China. The exchange traded repo market mostly coincides with financial market conditions and has high repo rates when the latest hot stocks are issued. In contrast, the interbank repo market generally follows the macroeconomic trend without high fluctuations. Therefore, the inter-bank repo market where Chinese central used reverse repo to adjust short-term market liquidity is less likely to reflect microeconomics issues in the ETF market.

In the classification of bilateral repo and tri-party repo,[5] a similar explanation is supported by Krishnamurthy et al. (2014). They believe that the full picture on the repo is yet to be assembled due to the lack of data on the bilateral repo market. A new US repo market survey reported by Gorton et al. (2020) shows that the bilateral repo was about three times large as a tri-party repo in 2004. The bilateral repo is popular in hedge funds, offshore institutions, and unregulated cash pools, while the data may be less available than in the regulated tri-repo market. It is premature to conclude whether repo significantly influences the financial market without considering non-reporting institutions.

Secondly, the determinant factors of repo quantities are more likely to consider balancing whole market capital demand and supply changes and aim to stable the financial market during this study period. Gabor (2016) believes that safe assets (government bonds), free repo market, and financial stability composite the repo

[5]Copeland et al. (2012) compare the US bilateral and tri-party repo market mechanics with details. The first developed repo market is bilateral, where cash and collateral transactions happen simultaneously between two sides. In a tri-party repo market, a clearing bank (e.g., Bank of New York and Mellon JP Morgan Chase) deals with transactions between cash providers and securities delivers.

trinity, which can not be satisfied at the same time. My results consist with the repo resilience and shock absorber hypotheses of Mancini et al. (2016). They found that European interbank repo spread, volume, and maturity have neither positive nor negative relationship with risk changes in financial market. Besides, Mancini et al. (2016) show that the secured interbank repo volume declined with excess liquidity providing by the central bank and a substitution effect exists between the repo market and unsecured money market. The central counterparty based repo market can play a role as a shock absorber.

The very wide confidence intervals in Figure 2.6 indicates that the sample uncertainty of impulse response estimation is high, and the accuracy of the impulse response coefficient estimation is low. Generally, confidence intervals are based on bootstrap methods. Benkwitz et al. (2000) argue that improper bootstrap method selection in a VAR model can cause a seriously distorted impression of the range of likely impulse responses. If $\sqrt{T}(\hat{\boldsymbol{q}} - \boldsymbol{q})$ converges as $T \to \infty$, $\sqrt{T}(\hat{\boldsymbol{q}}^{*} - \hat{\boldsymbol{q}})$ converges to the same limit distribution under suitable conditions (Hall, 2013). For example, the standard percentile intervals (CIs) requires that the limiting distribution of $\sqrt{T}(\hat{\boldsymbol{q}} - \boldsymbol{q})$ is symmetric about zero. Therefore, the impulse response coefficient estimation may not acquire its desired converge probability if the bootstrap distribution is asymptotically centred at $\hat{\boldsymbol{q}}$ adds a bias term rather than $\boldsymbol{q}$ precisely.

2.4.5 Potential Non-linearities over the Sample Period

It is common that Economic time series associate with non-linear features. Tong (1983) develops a threshold autoregressive model (TAR) to establish a linear model for different systems and aims to describe the nonlinear characteristics of variables. Hamilton (1989) proposes the Markov regime switching model, which focuses on non-linear state transition of a time series. There are plenty of extension models based on the studies of Tong (1983) and Hamilton (1989), which are widely applied in asymmetric empirical studies such as interest rates (Edwards and Susmel, 2001) and unemployment (Rothman, 1998).

Nonlinear time series models usually have rich dynamical structure. In Figure 2.7, the whole recorded repo operations in China starts from year 2000, which covers 1) the periods of mixed sell repo and reverse repo operations, 2) the single sell repo periods, and 3) the single reverse repo periods. The key feature of regime-switching models is that the generating mechanism varies with different time points and may be non-linear. The linear structural VAR model which is used in this chapter with invariant time parameters might be inappropriate if the sample periods are subject to shifts in regime. Alternatively, the general Markov switching vector autoregression model (MS-VAR) could be considered (Krolzig, 1998):

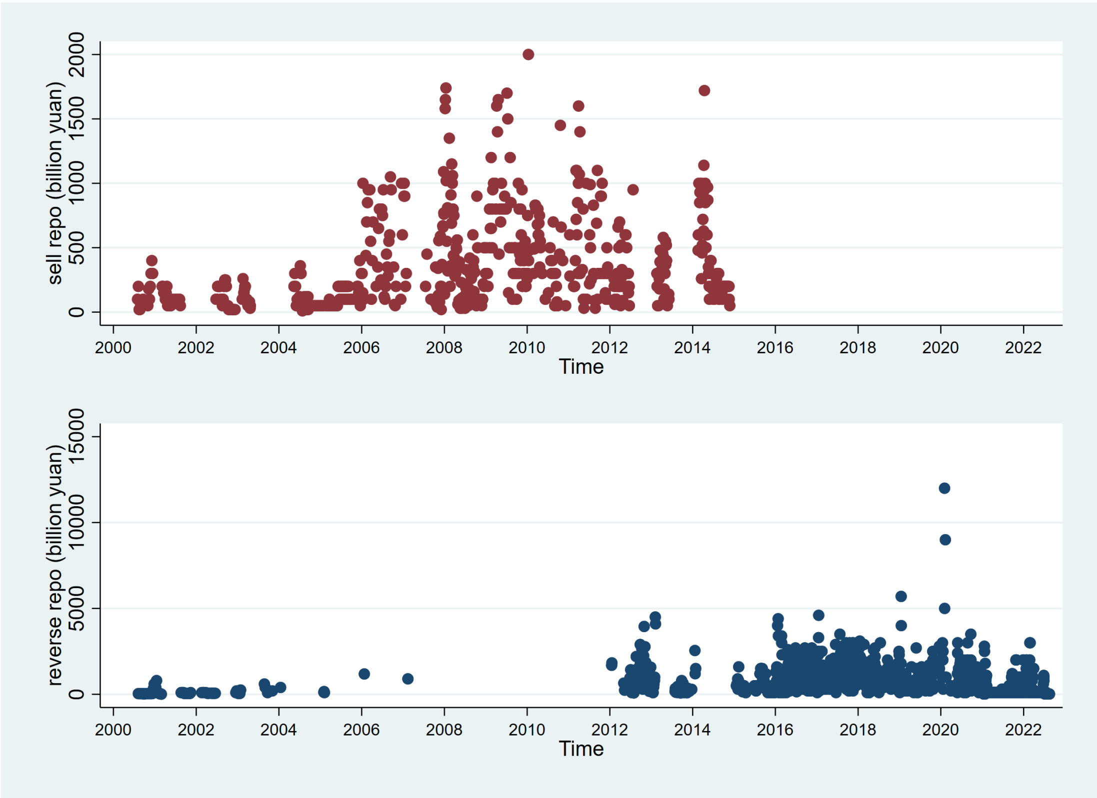


Figure 2.7: Sum of Repo Operations with Different Maturities

$$y_t = \begin{cases} v_1 + A_{11}y_{t-1} + \ldots + & A_{p1}y_{t-p} + \Sigma_1^{1/2} u_t, \quad if \quad s_t = 1 \\ & \vdots \\ v_M + A_{1M}y_{t-1} + \ldots + & A_{pM}y_{t-p} + \Sigma_M^{1/2} u_t, \quad if \quad s_t = M \end{cases}, \tag{2.41}$$

where $u_t \sim NID(\mathbf{0}, \boldsymbol{I}_k)$. For a discrete state Markov stochastic process, the unobservable realization of the regime $s_t \in \{1, 2, ..., M\}$ is governed by a discrete time. Define the transition probabilities to $p_{ij} = Pr(s_{t+1} = j | s_t = i)$, $\sum_{j=1}^{M} p_{ij} = 1$, $\forall_{i,j} \in \{1, 2, ..., M\}$. Let $\boldsymbol{P}$ represent the transition probabilities matrix. For example, a two-regime first order

MS-VAR has $\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} \boldsymbol{P}(s_t = 1|s_{t-1} = 1) & \boldsymbol{P}(s_t = 1|s_{t-1} = 2) \\ \boldsymbol{P}(s_t = 2|s_{t-1} = 1) & \boldsymbol{P}(s_t = 2|s_{t-1} = 2) \end{bmatrix}, p_{i1} + p_{i2} = 1$. MS-VAR model has its application limitations, because the transition mechanism is assumed to be discrete, and the regime transition is assumed to be determined by an exogenous unobservable Markov chain.

Non-linear models have less straightforward impulse response functions than linear models. The impulse response functions are independent on history in linear models, and the magnitude of shock does not change the time profile of the responses (Enders, 2014). However, the impulse response functions of non-linear models are history and shock dependent. Koop et al. (1996) introduce the generalized impulse response function for both linear and non-linear models. Specially, Ehrmann et al. (2003) develop the regime-dependent impulse response function to trace out the impact of fundamental disturbances on variables in Markov-regime dependent models. The impulse response function of the mk^2 regime-dependent model (e.g., equation 2.41) can be expressed to:

$$\frac{\partial E_t y_{t+h}}{\partial u_t} | s_t = \cdots = s_{t+h} = \theta_{ki,h}. \tag{2.42}$$

The k dimensional response vectors $\theta_{ki,1}, \ldots, \theta_{ki,h}$ predicts the response of endogenous variables. The regime-dependent impulse response function shows that the expected changes in endogenous variables at time $t + h$ to a one standard deviation shock to the kth fundamental disturbance at time t based on the condition of regime i. Obviously, impulse response functions in VAR and SVAR models do not consider regime-switching.

It is worth to investigate the non-linearities during 2000 to 2008 and 2012 to 2014 in Figure 2.7, where the Chinese central bank executives a mixed sell and reverse repo operations. Although sell repo and reverse repo is a pair of opposite operation, the same amount of sell repo may not have the exactly opposite effects as the same amount of reverse repo. Here, I consider a TAR model to illustrate non-linearities:

$$y_t = \begin{cases} a_1 y_{t-1} + \varepsilon_{1t} & y_{t-1} > 0 \\ a_2 y_{t-1} + \varepsilon_{2t} & y_{t-1} \leq 0 \end{cases}, \tag{2.43}$$

where $y_{t-1} = 0$ is a threshold, $y_{t-1} > 0$ represent reverse repo (release liquidity) and

$y_{t-1} < 0$ represent sell repo (withdraw liquidity). Each side of the threshold has a linear process, but the entire sequence $\{y_t\}$ is non-linear. In the reverse repo regime, the subsequent values of the sequence will tend to decay toward zero at the rate a_1; the decay rate is a_2 in the sell repo regime. The regime is less likely to switch from one to another if the variance of disturbance term is smaller. For example, Rothman (1998) applies TAR to the research American unemployment rate. His two-regime model shows that the shocks which increase unemployment do not decay to zero quickly. The U.S. unemployment is more persistent in the high-unemployment regime than the low-unemployment regime.

If we consider a linear AR(1) model $y_t = \rho y_{t-1} + \varepsilon_t$ with impulse response function $y_t = \sum_{i=0}^{\infty} = \rho^i \varepsilon_{t-i}$, the shocks will not change the time path of responses. Clearly, one unit shock has ρ impact on y_{t+1}, one unit shock has ρ^2 impact on y_{t+2}, and so on. The effects of a negative shock are simply the negative of those for positive shocks. However, in equation 2.43, the impulse response of one unit positive shock could have different time path with the impulse response of one unit negative shock. The size of shocks do not change regimes in the linear AR(1) model, but a large shock might cause regime-switching in the TAR model 2.43.

2.5 Conclusion

This chapter found that the short term liquidity released by reverse repo did not significantly influence ETFs mispricing level in the Chinese market. The Chinese central bank has frequently used reverse repo to adjust short-term liquidity positively since 2012. The reverse repo operations did not significantly impact Chinese ETF mispricing in the sample period (January 2016 to December 2018). The SVAR results implied that the Chinese ETFs mispricing responses were less sensitive to short-term quantitative open market operations—reverse repo. The market participants lack the motivation to arbitrage ETFs, which retained the average mispricing level consistently. Regime-switching models could be considered for the potential non-linearities over the sample period.

Table 2.3: VAR and SVAR Results

	VAR	SVAR
Mispricing		
Mispricing_1	0.826***	
	(-0.083)	
Mispricing_2	0.048	
	(0.107)	
Mispricing_3	-0.132	
	(0.107)	
Mispricing_4	0.177**	
	(0.080)	
Repo_1	0	
	(0.000)	
Repo_2	0.000	
	(0.000)	
Repo_3	0.000	
	(0.000)	
Repo_4	0.000	
	(0.000)	
Matrix (1, 1)		1.000
		(.)
Matrix (2, 1)		-76964.973**
		(-37121.838)
Matrix (1, 2)		0.000
		(.)
Matrix (2, 2)		1.000
		(.)
R-squared	0.9713	
Repo		
Mispricing_1	-3630.686	
	(38750.148)	
Mispricing_2	55195.362	
	(49683.873)	
Mispricing_3	11267.774	
	(49556.348)	
Mispricing_4	-9887.428	
	(37193.036)	
Repo_1	0.376***	
	(0.080)	
Repo_2	-0.091	
	(0.085)	
Repo_3	-0.077	
	(0.084)	
Repo_4	0.289***	
	(0.079)	
Matrix (1, 1)		0.001***
		0.000
Matrix (2, 1)		(.)
		0.000
Matrix (1, 2)		(.)
		587.473***
Matrix (2, 2)		(33.694)
R-squared	0.6994	
Observations	152	152

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

Chapter 3

Margin Trading, Short Selling, and Market Quality: Evidence from Chinese ETFs

Abstract

This study applies synthetic control methods to examine the effect of margin trading and short selling on Chinese ETFs. Using the staggered phase-in of the trading reform between January 2016 to December 2019 across Shanghai and Shenzhen markets, the synthetic control and difference-in-differences methods estimate the significant positive effect of the reform on liquidity in the treated ETFs, and inconsistent treatment effect on price efficiency and volatility. The placebo test and equivalence test jointly identify the existence of pre-trend and baseline randomization. No variables pass either diagnostic test, suggesting that the pilot program reflects the selection of treated ETFs.

3.1 Introduction

Unlike other emerging markets such as India which introduced margin trading solely (Kahraman and Tookes, 2017), the Chinese market adopted the dual introduction of margin trading and short selling. In 2019, the number of pilot ETFs had a rapid expansion, which provides a good sample for detecting the policy effects. I attempt to shed light on this issue by addressing two questions. What is the performance of these treated ETFs if margin trading and short selling restrictions remain? And, do they have constant treatment effects and improve market quality in the long term? Understanding how these trading constraints affect ETF market quality is essential because one crucial step to develop an advanced market is to facilitate a more complete market. Removing the margin trading and short selling bans on a list of ETFs may serve as the evidence that the China Securities Regulatory Commission has successfully improved market efficiency.

The effects of margin trading and short selling constraint reform on financial markets have been fiercely discussed. A number of empirical studies provide evidence that removing these trading restrictions can improve financial market efficiency by facilitating price and information discovery, return predictability, detecting financial fraud, and enhancing corporate governance. Chen et al. (2020); Xiangyou (2014); Xiong et al. (2017) report that pilot stocks have higher price efficiency, lower volatility and better return prediction in China. Deng and Gao (2018)find that short selling has monitoring power to inside corporation governance and reduce stock price crash risk. Fang et al. (2016) find that short selling helps firms to detect fraud and curb earnings management. Luo et al. (2020) find that short-sale deregulation can trigger shortable companies' tax avoidance intends in order to substitute costly external financing and generate extra internal funds for future investments.

Opponents argue that the removal of margin trading and short selling bans leads to stock value losses of pilot firms, liquidity decreases, and higher volatility (Ni and Yin, 2020; Sharif et al., 2014). During the market crisis period, margin trading and short selling are usually blamed for amplifying instability or the destabilizing stock market Lv and Wu (2019); Zeng et al. (2016). The massive financial market flu actuation in 2015 led to immediate responses by Chinese regulators. The corresponding policies include increasing the margin ratio from 50 per cent to 100 per cent, limiting the total amount of margin trading and short selling under four times of a securities company's net capital, and requiring short-sellers to repay their securities from the next trading day after short selling. Many developed markets such as the United

States, the United Kingdom and Australia adopted emergency regulation of short selling during from mid-September to late October 2008 to ensure the stability of the financial system(Sheehan, 2012).

The Chinese ETF market has had less attention than the stock market, and there is a lack of empirical results from a market-wide aspect. ETF short sellers are more likely to borrow securities from dealers than stock short sellers due to the flexible creation and redemption process. There are two safety features are protecting ETF short-sellers (Asness, 2004): Firstly, unlike aggressive short sales, most ETFs short sales aim to reduce total risk in a portfolio or offset long market risk. Index arbitrageurs holding long features or basket investments have a strong hedging motivation to short the underlying stocks, and ETF shorting is an ideal method, especially as inverse ETFs are very limited in China. Secondly, ETFs can be created by an authorized participant in any trading days to avoid a potential short squeeze, which contracts to most corporate stocks with fixed share outstanding in a long time.

The amount of short selling is more than the amount of short selling in China, but it is hard to conclude that margin trading must dominate the combined effects and eliminate short selling effects. This chapter includes 9 treated ETFs and 58 controlled ETFs, and the monthly data set covers from January 2016 to December 2019. I find greater trading volume and turnover in the ETF market when margin trading and short selling are allowed. No evidence supports that margin trading and short sales restrictions affect ETF price efficiency. The estimated price treatment effect is not significant, although the coefficient of ETF premium from the regression is positive. Consistent with the overpricing hypothesis (Miller, 1977), there is a slight decline in ETF return rates after removing short sales constraints. I also observe that the short term return decline is associated with a slight volatility decrease. The downward price adjustment of treated ETFs suggests that investors require lower expected returns on ETFs when margin trading and short selling transactions are possible, and the market is more stable than before. However, the synthetic control method shows no persistent treatment effects of return and volatility on the ETFs with both margin trading and short selling qualifications. The failed placebo and equivalence tests indicate that the existence of pre-trend and the pilot ETFs are not based on randomization.

It is noticeable that the effects of this margin trading and short selling trading reform also depends on confounding factors such as investor trading behaviour, market situations, regulatory policies and so on. The commonly used DiD method cannot answer whether these confounding factors matter. Besides, the change of eligible conditions and updated designated lists published in different dates and frequencies, which cannot provide a clear cutoff for employing a regression discontinuity design. Taking consideration of these limitations, I apply two different extended synthetic control methods (Liu et al., 2020; Xu, 2017) in which I focus on the counterfactual estimation. Different from event studies, DiD method and propensity score matching in the individual level, synthetic control methods avoid the subjective selection problem and calculate counterfactual estimators to generate more objective treatment effects from the market-wide aspect. Moreover, the generalized synthetic control method can be used in the case of treatment reversal, which allows researchers to keep more treated units. The findings directly show how margin trading and short selling affect ETFs after relaxing restrictions, and what these ETFs' performance would be without lifting bans. Thus, we can see whether there are persistent treatment effects and reduce the bias caused by different sample period selection.

The rest of this chapter proceeds as follows: Section 3.2 discusses relevant studies. Section 3.4 describes the methodology adopted. Section 3.3 presents the data collection and summary statistics. Section 3.5 shows empirical results and discussions. Finally, the conclusions are presented in Section 3.6.

3.2 Literature Review

The relationship between capital constraints and market liquidity has been commonly discussed. An influential theory model proposed by Brunnermeier and Pedersen (2009) points that tight capital liquidity can cause market illiquidity, especially in times of financial crisis. When prices decline consistently, investors tend to decrease their leverage positions to raise more capital due to declined funding liquidity, which reinforces capital illiquidity and market illiquidity. The effect on market liquidity is small if a marginal change in the capital is far from the investor capital constraints, but a close approach to investor capital constraints can cause liquidity to dry-up suddenly. Garleanu and Pedersen (2007) provides a new insight into liquidity and risk management. Their model shows that tight risk management lowers market liquidity, and prices drop because liquidity is priced.

In terms of short selling theory models, Ausubel (1990) argues that short selling permission can reduce trading volume because uninformed investors will avoid taking participate in the market with a great number of informed counterparts. Following their model, a lower proportion of informed traders exist in the market with short selling constraints, and uninformed traders are supposed to be liquidity suppliers. The later theoretical model developed by Scheinkman et al. (2003) confirms that short-sale constraints lead to price bubbles and high trading volume. An opposite conclusion is drawn by Diamond and Verrecchia (1987). They predict that a ban on short selling increases the bid-ask price, which indicates that the absence of short selling impedes liquidity of individual stocks.

Empirical studies about the influence of margin trading and short selling on market liquidity are also highly controversial. Ye et al. (2020) use the effective spread to capture the liquidity of individual stocks and provide impressive evidence: margin trading increases stock liquidity and short selling damages stock liquidity in a regular market, while the two types of leveraged trading switch effects during market downturns. Another direct liquidity measurement is trading volume, which is applied by Zhou and Li (2019) to examine the influence of the two-sided market[1]. They construct an agent-based artificial market model and conclude that a dual introduction of margin trading and short selling is better than a separate introduction in terms of market stability and efficiency. Their evidence shows that stock volume increases in both markets, but the volume increases much more slowly in the two-sided market. In the aspect of price impact benchmarks, Amihud (2002) develops an illiquidity measure, which is defined as the average across stocks of the daily ratio of absolute stock return to dollar volume. The Amihud price impact ratio is widely applied as return and trading volume with low frequency is easy to acquire in most markets. However, Xiangyou (2014) argues that this Amihud price impact ratio may not be suitable to emerging stock markets such as the Chinese market, because the zero

[1]The two-sided market means both margin trading and short selling activities are permitted

trading volume may occur in some days. They propose an alternative illiquidity ratio for ETFs liquidity measuring, which is defined as averaged price amplitude in a certain period dividing the lowest trading volume in the period. Goyenko et al. (2009) analyse liquidity proxies performance by different data frequency and find that the new effective (realised) spread measures show better performance than other measurements in monthly and yearly data frequency samples.

Price efficiency is another essential indicator of policy evaluation literature, while it has different measurements and shows mixed conclusions. Lv and Wu (2020) find that increased margin trading activities associate with higher price adjustment speed and lower information content. Their different price efficiency proxies show that margin trading leads to a more efficient market or a lower market efficiency. As the empirical evidence of margin trading influence on price efficiency is mixed, some studies consider this question using experimental asset markets. Ackert et al. (2006) find that a ban on margin buying dampens price bubbles. Füllbrunn and Neugebauer (2012) state that margin trading prohibition narrows the price deviations from fundamental values. These experimental results indicate that margin trading tends to cause price bubbles and distort market efficiency.

As short sellers face high transaction fees when conducting short sales, they would engage in this high costs activity only if they have negative information about security future returns. Information content and adjustment speed are essential to investigate price efficiency. An essential theory model (Diamond and Verrecchia, 1987) analyses short selling constraints from the aspect of information adjustment speed. Diamond and Verrecchia (1987) argue that short selling constraints reduce the adjustment speed of prices to private information, especially in the aspect of bad news. They claim that short constraints can improve information adjustment rate based on their theoretical model, although the effects are unlikely to dominate the market. Supporting this model, Chen and Rhee (2010) reports that stocks without short-sale constraints show better price adjustment ability than stocks with short-sale prohibition in the Hong Kong market. A recent study in China (Chen et al., 2020) supports that price efficiency for stocks lift the bans in the fifth-round is much higher than those that do not lift. Another stream of studies explores the impact of margin trading on price adjustments. Garleanu and Pedersen (2011) develop a margin CAPM model. It is a standard CAPM model which adds a margin requirement multiplied margin premium. As margin requirements are positive in real world and the margin premium is defined as shadow cost of funding risk-tolerance agents multiplied by the relative importance of agents, the extended part of the margin CAPM model would not be negative. In their model, high-margin assets have a higher required return than low-margin assets, which means margin constraints lead to assets undervaluation. In other words, the introduction of margin trading would lead to prices increasing.

A generally argued reason for securities lending and borrowing is that investors engage in short selling have a belief of assets overvaluation. Miller (1977) develops an influential theory model about short selling constraints and assets overvaluations. The absence of short selling prevents negative information from passing on stock prices, and pessimistic investors can not gain profits by declined stock prices. Hence, optimistic investors cause an upward bias to stock prices without short-sale constraints. Empirical studies (Dechow et al., 2001; Jones and Lamont, 2002) support that when short-sale constraints are allowed, overvaluations become less severe, suggesting that short sellers are plausibly to keep prices in line. In the case of China, Xiong et al. (2017) find the successive short selling allowances improve price efficiency and have positive influence strengthens over time. Chan et al. (2010) study short-sale constraints on Hong Kong and mainland China, and find that removing short-sale constraints results in a decrease in the price of pilot stocks relative to their peers.

The releasing of margin trading and short selling has opposite effects on security prices in theory, in which margin constrains connect with assets undervaluation (Garleanu and Pedersen, 2011) whilst short-sale constrains relate to overvaluation (Miller, 1977). In the case of Chinese market, margin trading and short selling are introduced at the same time. There is ambiguity over whether ETFs with margin trading and short selling qualification are undervalued or overvalued and which effect dominates the effect of the average price. Although the amount of margin trading is much higher than short selling, recent empirical results show a dominate short selling effect on asset prices in the Chinese market. For example, Chang et al. (2012) focus on the first margin trading and short selling list in the Chinese stock market. They report an average abnormal return of -44.5bps with the designated stocks, and the accumulated negative returns of these stocks last for 60 trading days after removing the ban. Sharif et al. (2014) discuss the combined effect on margin trading and short selling in the Chinese market, and think that the declined stock prices on average can be explained by dominated short selling effects over margin trading effects.

Mainstream views of the macroeconomics thinks that the real economy and finance can be completely separated, and finance only acts as a lubricant in the economy without any substantial impact on the real economy if financial friction is not considered David (2018). However, the real world is opposed to the benchmark neoclassical model which financial market is not frictionless. Financial market volatility indicates market uncertainty and risk and has impacts on macroeconomic sectors such as consumption and investment.

The life-cycle and permanent income hypothesis (Blanchard and Fischer, 1989) are the major theories of how consumption relate to financial asset price volatility, which regard consumption as a function of asset. When asset prices increase, consumers can sell or pledge assets to acquire cash flow and increase the current consumption. Consumers can also change their margin consume propensity by the impacts of asset price volatility on future expected income. Bernanke and Gertler (2000) state that the effects of asset price changes on the economy through balance sheets channel (e.g., households, firms, and financial intermediaries). In sum, asset price changes mainly affect consumer demand through changes in consumers' wealth balances, and then have an impact on the macro economy.

Some researchers (Bernanke and Gertler, 2000; Bordo and Jeanne, 2002; Semmler and Zhang, 2007) suggest that the volatility of asset prices such as house prices and stock prices should be included in inflation expectations and the central bank forward-looking interest rate rules. The expansion of asset bubbles is generally accompanied by high growth in monetary credit, especially during periods of economic upswing. The central bank and policy makers should strengthen the monitoring and analysis of monetary credit, pay attention to the future inflation information reflected in asset price fluctuations, and build a relationship between asset price changes and monetary policy adjustments.

The financial business cycle theory Gertler and Kiyotaki (2010); Kiyotaki and Moore

(1997) thinks that moral hazard and adverse selection problems exist in financial markets due to financial frictions and discusses the relationship between finance cycle and investment. Financial institutions often ask companies to provide assets as collateral when they issue loans. When the economy has negative shocks and companies suffer balance sheet deterioration, financial institutions will shrink lending scale. Companies might have to sell assets or reduce investments for paying loans, which in declines asset prices, deteriorates companies' balance sheet, and further shrink loans. Besides, Bloom et al. (2007) state that the waiting value of investment increases under policy and market uncertainty, and rational investors usually reduce or delay investments to avoid risks.

As for the impact of margin trading on market volatility, studies usually discuss from capital constraints and changes of margin requirements. Brunnermeier and Pedersen (2009)'s model shows that margins can push market illiquidity further and increases volatility. This happens when margin-setting financiers are not confident about market fundamental judgments and little price volatility can make financiers raise margins. Chowdhry and Nanda (1998) develop a model and discuss whether margin trading causes market instability from the view of supply and demand equilibrium. A decrease of price declines the capacity of investors to purchase their desired amount of risky assets, which makes the price decreases rationally as risk-averse investors reduce the demand of risky assets and ask higher risk premiums than before. Similarly, a rise in price increases purchase capacity and wealth of investors and make them more risk-tolerant. The price increases are rationally due to increased demand. Although margin trading can cause price instability as a rational outcome based on this theory model, they also point out that the market is stable if margin buying quantity is small and low heterogeneous of investor risk preference.

Theories about whether short-sale activities cause market volatility are controversial. On the one hand, Scheinkman et al. (2003) propose a model based on short-sale constraints and heterogeneous beliefs associated with overconfidence. They claim that the absence of short selling can generate excessive trading, unwanted volatility and price bubbles. Anufriev and Tuinstra (2013) establish an asset-pricing dynamics model with heterogeneous beliefs and introduce short selling constraints by imposing trading costs for short selling risky assets. If assets are overvalued, transaction costs will increase price volatility. On the other hand, Mizuta et al. (2015) agree with that regulations such as short-sale limitation can prevent overshoot in a bubble collapse and make the market stable, but their model also points out short selling regulations and uptick rules cause transaction prices excess fundamental values in normal market situation.

Throughout the economic empirical literature, the impact of margin trading and short selling on market volatility is usually discussed separately, and mixed results leave this issue elusive. Hardouvelis and Theodossiou (2002) and Chou et al. (2015) discuss the relationship between margin requirements and volatility among different market scenarios and find that the changing of margin requirements causes market volatility. A recent study (Xie and Jia, 2019) on the Chinese market finds that the first two stages of margin trading activities increase market volatility. However, the latest pilot results show a positive margin trading effect on stabilizing the market. Lv and Ruan (2018) believe margin buying activities reduce price crash-prone in bad times, while margin covering activities amplify price crashes in all market scenarios.

Research on how short selling impacts the volatility of the stock market also have not reached an agreement. Chang et al. (2007) focus on the effect of short selling lift on the Hong Kong market and believe that short selling enhances market volatility during the financial crisis in 2009. Short selling activities might be unrelated to market prices and fundamental values, whose primary purpose is to hedge the risk of current assets and use inexpensive beta exposure such as ETFs for a better portfolio performance (Tuchschmid et al., 2012). Thus, it is not surprising that many empirical results show a positive effect of short selling on reducing ETFs volatility (Chang et al., 2014; Daouk and Charoenrook, 2005; Qiong, 2011; Xiangyou, 2014).

3.3 Data

3.3.1 Background

Margin trading and short selling activities were banned in China by the Security Act in 1999. This ban was ended in January 2006, then the China Securities Regulatory

Commission (CSRC) enacts various laws to set the dual introduction of margin trading and short selling in a start-up phase. After four years of preparation, in March 2010, Shanghai and Shenzhen stock exchange formally accept 90 stocks and make margin trading and short selling to an operational phase. The practice in the Chinese ETFs market is permitted in December 2011, which only accepts 7 ETFs. Compared with the stock market, the expansion speed of margin trading and short selling in the ETF market is relatively slow in the following six years. By August 19, 2019, there are 63 ETFs and 1600 stocks allowed to do margin trading and short selling. At the time, ETFs margin balance increased from 0.5 percent in 2011 to 12 per cent in 2019. The positive expansion in 2019 is the largest one since China's stock crash in 2015, either in terms of the list updating frequency or the number of new added ETFs.

3.3.2 Data Collection

The expanded pilot list enables us to consider an average effect by panel data and reduces limitations of research methods selection. Although data is available before 2016, I reduce pre-treatment periods to avoid the stock market crash in 2015. Another reason is that the number of ETFs in the early stage is much less than the number of active ETFs after 2018, limited ETFs are available for control group may lead to poor synthetic control effects. Similarly, I cut the post-treatment periods in 2020 for excluding market fluctuations due to the coronavirus pandemic possible influence. This chapter concentrates on the dual introduction effect on ETFs in 2019. There are 21 ETFs acquire margin trading and short selling qualification in 2019, and more than 100 active ETFs do not have this qualification.

However, only 9 ETFs are included in the treated group, and 58 ETFs are selected into the control group. Table 3.1 shows 5 treated ETFs from the Shenzhen Stock Exchange and 4 treated ETFs from the Shanghai Stock Exchange after selecting. These five ETFs track traditional and relatively large indexes, two commodity ETFs track the Gold index, two stylish ETFs track information industry and health industry, respectively. The control group is listed in Appendix Table 3.A1. The data collecting standards of this chapter explain why significant data loss happens. Firstly,

Table 3.1: Treated Units

Ticker	Launch date	Joined date	Tracking index	Market
159910	01aug2011	14jan2019	Shenzhen fundamental 120 index	Shenzhen
159916	08sep2011	09july2019	Shenzhen fundamental 60 index	Shenzhen
159934	29nov2013	14jan2019	Gold 9999	Shenzhen
159937	14aug2014	14jan2019	Gold 9999	Shenzhen
159939	08jan2015	15apr2019	All share information index	Shenzhen
510580	27aug2015	08jul2019	CSI 500 index	Shanghai
510710	08oct2015	15apr2019	Shanghai 50 index	Shanghai
512010	23sep2013	15apr2019	CSI 300 medical and health index	Shanghai
512510	13may2015	08jul2019	CSI 500 index	Shanghai

the total sample excludes bond ETFs since their par value is much higher than normal ETFs. Secondly, the difference between ETFs launch date and the date they are entering the pilot program is larger than six months. Thirdly, controlled ETFs are active in the sample period. Fourthly, in order to preserve enough post-treatment periods, ETFs which join the pilot program after August 2019 is not included. Lastly, although the model applied in this study allows the cases of treatment reversal, I only consider ETFs which join margin trading and short selling list once and never be deleted or selected again later.

This sample covers from January 2016 to December 2019. Daily data on ETFs return rates, turnover rates, trading volume, market prices, and net asset values are collected from the China Stock Market and Accounting Research Database (CSMAR). The adjustment list of ETFs margin trading and short selling qualification is extracted from Research Set (RESSET). Daily ask prices and bid prices come from Thomson Reuters Datastream. The following analysis uses monthly data which is averaged by these daily data.

3.3.3 Descriptive Statistics

Trading volume, turnover and spread

Figure 3.1 describes the averaged monthly trading volume of all sample ETFs. The dark blue lines represent the liquidity of treated ETFs during post-treatment, and the light blue line represents the liquidity in pre-treatment periods. The controlled ETFs are shown in grey lines. Figure 3.1 shows the first liquidity indicator—trading volume. The three ETFs have kept an obvious increasing trend after joining margin trading and short selling list, while the trading volume of the rest five ETFs shows minimal influences after joining the list. Except two ETFs have significant higher trading volume than controlled ETFs in pre-treatment periods, other treated ETFs have similar quantities with controlled ETFs in pre-treatment periods. It is noticeable that almost all treated units have a moderate rising around a half year before acquiring margin trading and short selling qualification.

However, the trading volume might be less comparable if we discuss liquidity among different stocks and funds, especially their sizes are not in the same magnitude. Alternatively, turnover has treated as a proxy for liquidity in the assets pricing study, which is calculated as trading volume over shares outstanding. Following Datar et al. (1998), I measure the monthly turnover rate of every ETF by average daily turnover. Similar to the trading volume in Figure 3.1, turnover in Figure 3.2 shows that there are two lines obviously higher than others in pre-treatment time. This indicates that these two ETFs may not be ideal control units and cannot generate accurate counterfactual estimators in the later synthetic control analysis.

As this study uses monthly frequency data, I calculate quoted spread as a supplementary liquidity proxy: $Spread_{it} = [(Ask_{it} - Bid_{it})/Mid_{it}] \times 100\%$, where Ask_{it} is the ask price of ETF_i at day t, Bid_{it} is the bid price of ETF_i at day t, and Mid_{it} is the midpoint of these two prices at day t. Then, following Fong et al. (2017), I average daily quoted spread by time weighting intraday spreads. Figure 3.3 shows all sample monthly spread. Both treated group and the controlled group have dispersed spreads in pre-treatment periods, while spreads of treated ETFs are significantly centralized in post-treatment periods. Intensively, margin trading and short selling reduce ETFs spreads without obvious individual treatment effect differences.

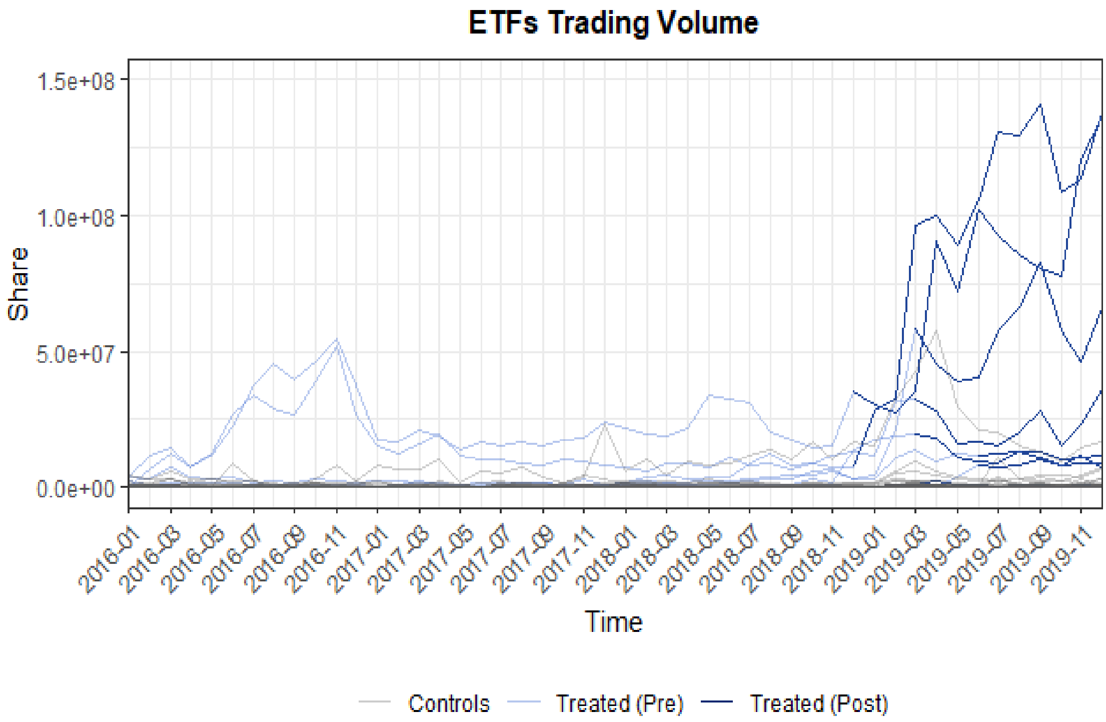


Figure 3.1: Trading Volume of Treated and Controlled ETFs

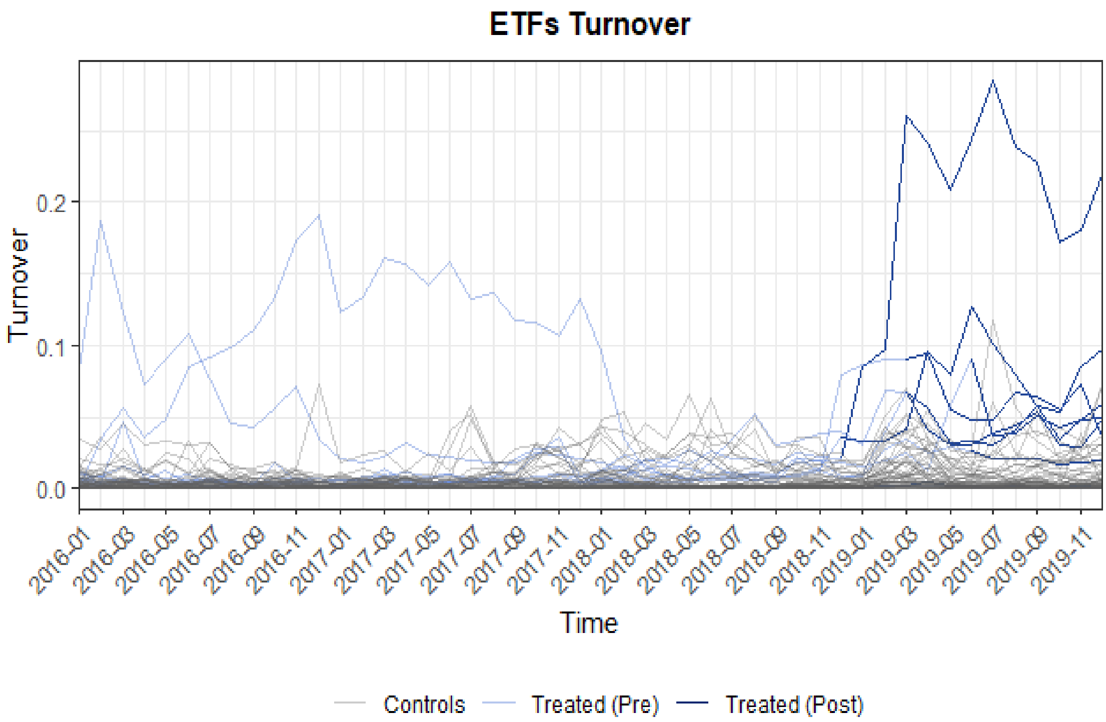


Figure 3.2: Turnover of Treated and Controlled ETFs

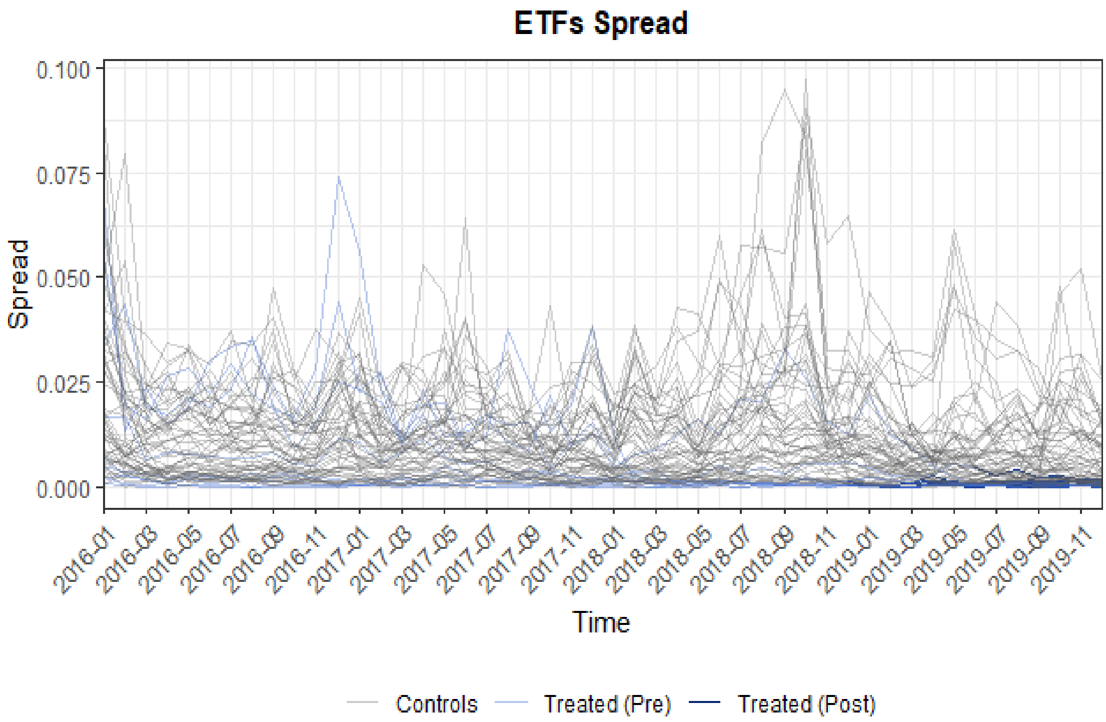


Figure 3.3: Spread of Treated and Controlled ETFs

Price efficiency and return

ETFs have two prices, the one is the secondary market trading price and the other is NAV, which bases on the value of underlying securities. Gallagher and Segara (2005) regard persistent price deviation as price efficiency. Following the ETFs price efficiency measurement of Lin et al. (2006), I measure efficiency as: $E_{it} = [(ETF_{it} - NAV_{it})]/NAV_{it} \times 100\%$, where NAV_{it} is the closing price of ETF_i on day t and ETF_{it} is the market price on day t. In Figure 3.4, both treated and controlled ETFs show relative flat price deviations in 2019, which is difficult to attribute the generally reduced price deviations to treatment effects.

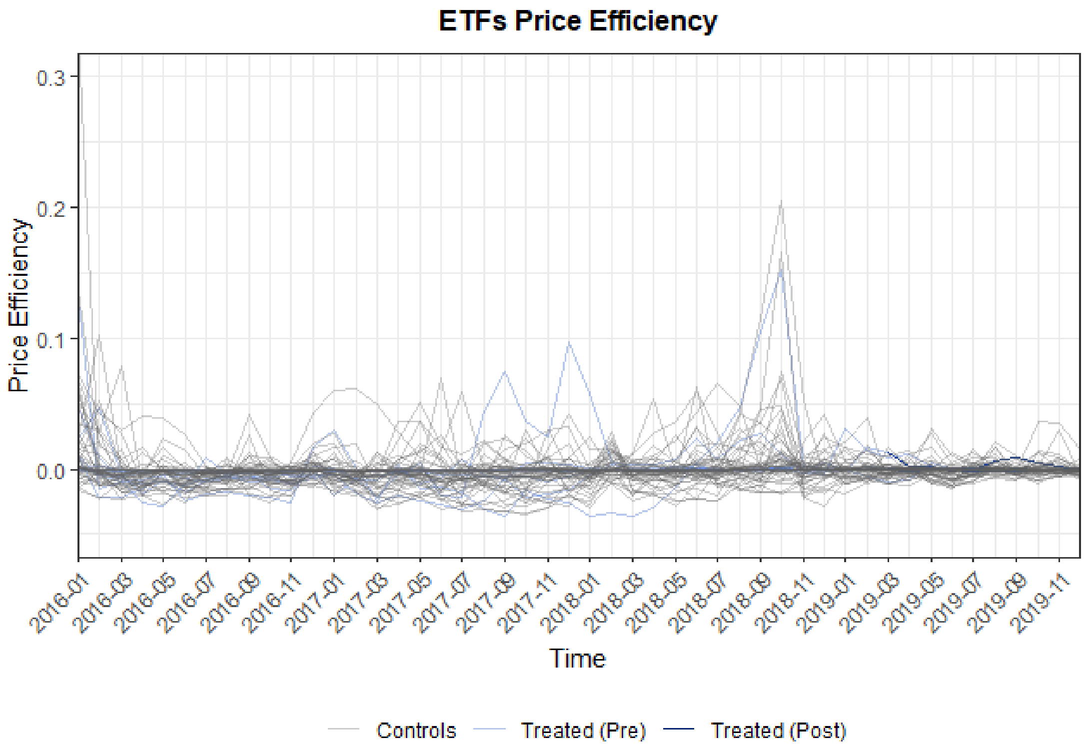


Figure 3.4: Price Efficiency of Treated and Controlled ETFs

Some researchers (Chang et al., 2014; Diether et al., 2009) argue that short sellers are informed traders and short selling activities can predict future stock returns. This paper also examines whether ETFs return is affected by the lifting of margin trading and short selling bans. Follow the common ETFs return calculation of Aber et al. (2009), which uses the current ETFs market price and market price in the previous day: $Return_{it} = [(ETF_{it} - ETF_{it-1})/ETF_{it-1}] \times 100\%$. Figure 3.5 shows a less fluctuate return trend in post-treatment periods comparing with controlled ETFs in the first quarter of 2019, while return of treated ETFs is similar with controlled ETFs during this period.

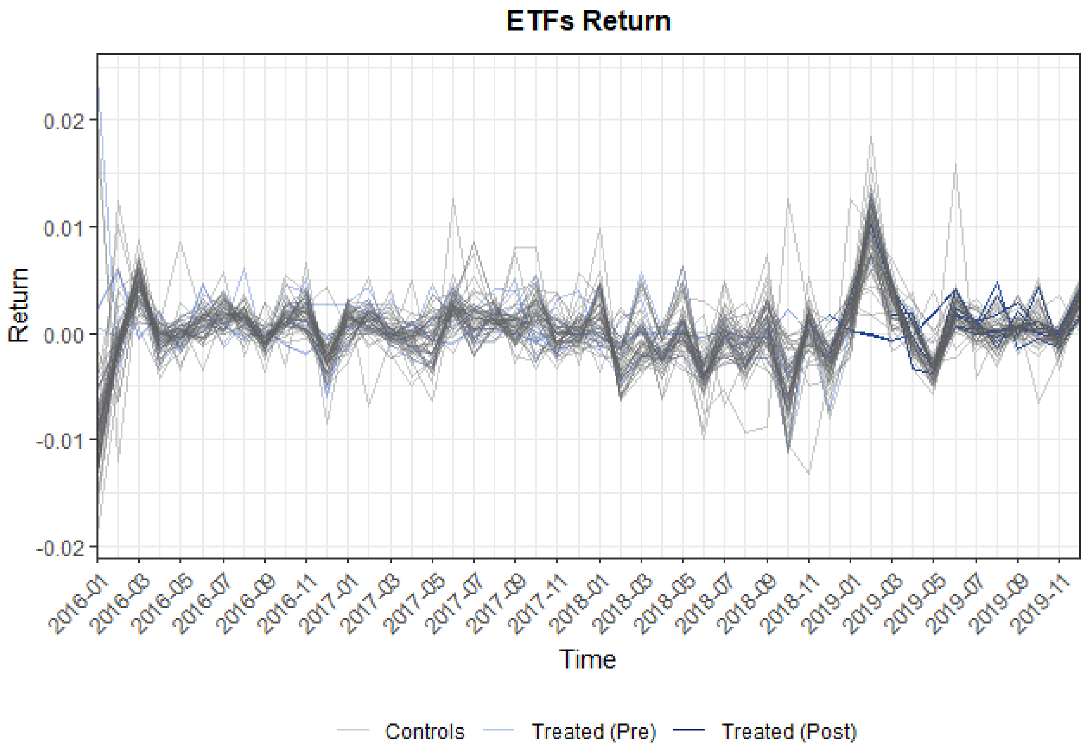


Figure 3.5: Return of Treated and Controlled ETFs

Price volatility

Following Aber et al. (2009), I define the ETFs price volatility as: $V_{it} = [(Highest\ price_{it} - Lowest\ price_{it})/Lowest\ price_{it}] \times 100\%$, where the $Highest\ price$ and $Lowest\ price$ is the intraday highest price and lowest price of ETF_i at day t, respectively. The monthly frequency data in Figure 3.6 is averaged by daily volatility. Figure 3.6 does not show a unified decline trend of price volatility, and especially, the ETFs have relatively low price volatility in pre-treated periods and increase price volatility slightly after entering margin trading and short selling.

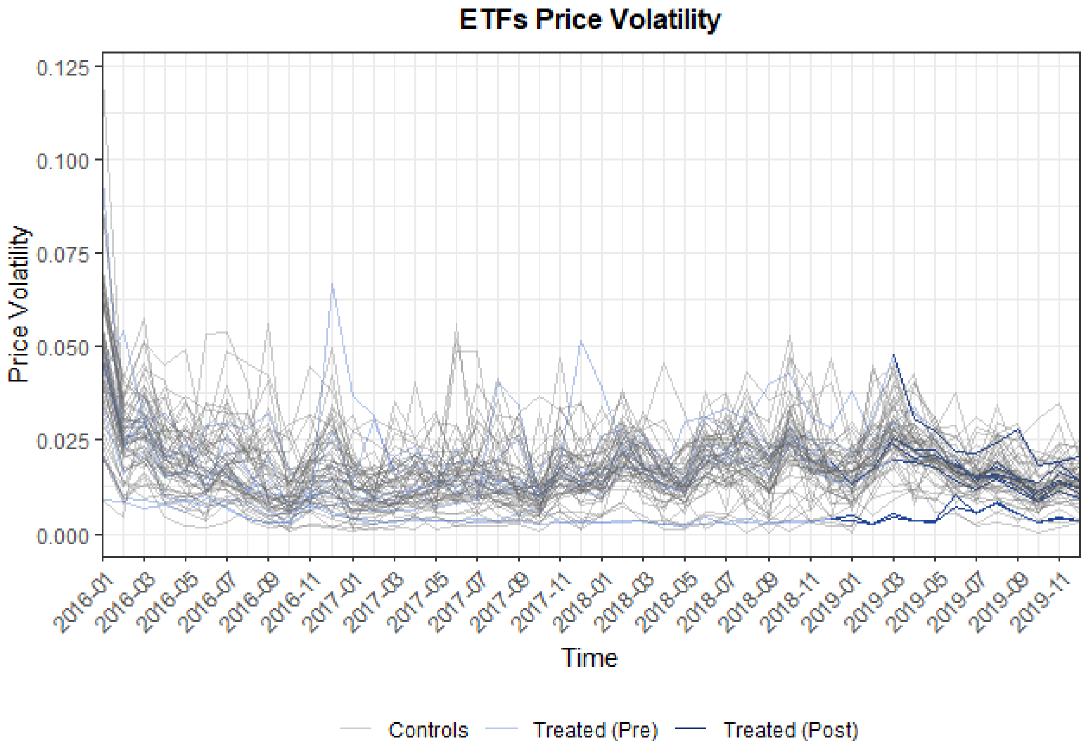


Figure 3.6: Price Volatility of Treated and Controlled ETFs

3.4 Methodology

3.4.1 Counterfactual Estimators

The traditional synthetic control method considers one treated unit under a strongly balanced panel frame and strictly assumes all units have parallel trends during observed periods. Xu (2017) introduces a generalized synthetic control method to address the multiple treated units problem and release the strict parallel trend assumption. It generates counterfactual predicts based on minimizing the distance between treatment units and control units in pre-treatment time.

This chapter uses the counterfactual estimates method of Liu et al. (2020). Compare with the generalized synthetic control method (Xu, 2017), the counterfactual estimates method (Liu et al., 2020) allows treatment reversal and provides two diagnostic tests, and is well incorporated with imbalanced panel data and reversal treatment units. It emerges commonly employed methods, such as fixed-effect counterfactual estimator, the interactive fixed-effect counterfactual estimator and the matrix completion estimator. There are two main advantages of their counterfactual estimates method: 1) allows dynamic treatment effect and the constant treatment effect assumption of conventional fixed effects model is relaxed; 2) interactive fixed counterfactual estimator and matrix completion estimator can handle time-varying confounders. For convenience, I consider a balanced panel in which there are N units observed in time periods $t = 1, ..., T$. Let T_{tr} and T_{co} be the time periods of treatment group and control group, respectively. Thus the total number of units N can be written as $N = N_{tr} + N_{co}$. Suppose the potential outcome in period t is y_{it} for all units $i = 1, ..., N$, and for all $t = 1, ..., T$, where $y_{it}(0)$ and $y_{it}(1)$ correspond to potential outcomes for $D_{it} = 0$ and $D_{it} = 1$, respectively. Donate the treatment status as D_{it} (equals to 1 if the unit i enters into the treatment period and equals to 0 if the unit does not receive any treatment). ε_{it} is the error term which has zero mean. $\delta_{it} = y_{it}(1) - y_{it}(0)$ is the treatment effect of unit i in period t. Following Liu et al. (2020), the first assumption shows the functional form.

Assumption 1

$$y_{it}(0) = f(\mathbf{X}_{it}) + h(\mathbf{U}_{it}) + \varepsilon_{it},$$

where $\mathbf{X_{it}}$ a vector of the exogenous covariates, $\mathbf{U_{it}}$ is the unobserved attributes, and both parametric $f(\cdot)$ and $h(\cdot)$ functions are known.

Assumption 2

$$\varepsilon_{it} \perp\!\!\!\perp \{D_{js}, \mathbf{X_{js}}, \mathbf{U_{js}}\} \quad i, j \in \{1, 2, ..., N\} \quad s, t \in \{1, 2, ..., T\} \quad \forall i, j, s, t.$$

The second assumption requires error term of any unit at any time is independent with treatment states, observed exogenous covariates and unobserved attributes, which rules out indirect treatment effect estimation. Blackwell and Glynn (2018) suggest that strict exogeneity corresponds to baseline randomization and researchers should consider sequential ignorability when it is not satisfied in their settings. The second assumption rules out the contagion and infectiousness effects[2] which are

[2]Ogburn and VanderWeele (2017) summarized the conception of contagion and infectiousness effects and further demonstrated the possibility of testing these two effect which are firstly introduced by VanderWeele et al. (2012): "The contagion effect is the indirect effect that vaccinating one individual may have on another by preventing the vaccinated individual from getting the disease and thereby from passing it on. The infectiousness effect is the indirect effect that vaccination

commonly exist in vaccination treatment estimation.

A number of studies build assumption upon the presence of interference (Aronow and Samii, 2017; Hudgens and Halloran, 2008; Sobel, 2006; Ye et al., 2020), but it is not included in our discussion. This paper follows the classical stable unit treatment value assumption (Rubin, 1980), which means the outcome of unit i is independent on the treatment of other units, and the outcome of unit i at time s is independent on its own treatment status at time t.

Assumption 3

$$h(\mathbf{U}_{it}) : h(\mathbf{U}_{it}) = L_{it}, \quad rank(\mathbf{M}_{N\times T}) \ll min\{N, T\}.$$

In equation 3.3 and 3.4, $\boldsymbol{M}_{N\times T} = \boldsymbol{\Omega}_{N\times r}\boldsymbol{F}_{r\times T}$ $(rank(\mathbf{M}_{N\times T}) \ll min\{N, T\})$ is low dimensional decomposition. A low-rank matrix contains a lot of redundant information, which is helpful to missing data recovery and data feature extraction. A low-rank matrix is a non-convex function and it is hard to get solutions. Nuclear Norm is applied in this estimation because it is a nearly convexity of a low-rank matrix and commonly used in matrix completion (Athey et al., 2021).

The two-way fixed effects counterfactual estimator

If unobserved factors are fixed over time, the two-way fixed effects counterfactual estimator (FEct) can be take into consideration. We can rewritten the function form as:

$$y_{it} = \delta_{it}D_{it} + {x_{it}}'\beta + \mu_i + \lambda_t + \varepsilon_{it}, \tag{3.1}$$

where the x_{it} is a $(p \times 1)$ vector of observed covariates, and β is a $(p \times 1)$ vector of unknown coefficients. In this FEct model, μ_i represents the individual-specific component and λ_t represents the time-specific component, respectively; and $\boldsymbol{\varepsilon}_{it}$ is a $(T \times 1)$ vector and has zero mean. Liu et al. (2020) remind that the FEct regards observations under treatment condition as missing values and can estimate dynamic treatment. If treatment effect is constant ($\delta_{it} = \delta$ for all i and t), equation (3.1) will

might have if, instead of preventing the vaccinated individual from getting the disease, it renders the disease less infectious, thereby reducing the probability that the vaccinated infected individual transmits the disease, even if infected."

be the conventional two-way fixed effects model.

The interactive fixed-effects counterfactual estimator

If unobserved time-varying confounders exist, conventional DiD will lead to biased estimators (Gobillon and Magnac, 2016). To address this issue, we can apply the the interactive fixed-effect counterfactual estimator (IFEct) model, which incorporates unit-specific factor loadings interacted with time-specific factors:

$$y_{it} = \delta_{it} D_{it} + x_{it}{}' \beta + \omega_i{}' f_t + \varepsilon_{it}. \tag{3.2}$$

The factor component is $\omega_i{}' f_t$ ($\omega_i' f_t = \omega_{i1} f_{1t} + \omega_{i2} f_{2t} + ... + \omega_{ir} f_{rt}$) that captures time-varying trends, where ω_i is an $(r \times 1)$ vector of unknown factor loadings ($\omega_i = [\omega_{1i}, ..., \omega_{ir}]'$ and $\boldsymbol{\Omega} = [\omega_1, \omega_2, ..., \omega_N]'$), f_t is an $(r \times 1)$ vector of unobserved common factors ($f_t = [f_{1t}, ..., f_{rt}]'$ and $\boldsymbol{F} = [f_1, f_2, ..., f_T]'$), x_{it} is a $(p \times 1)$ vector of observed covariates, and β is a $(p \times 1)$ vector of unknown coefficients, $\boldsymbol{\varepsilon}_{it}$ is a $(T \times 1)$ vector and has zero mean. It is easy to see that IFEct of equation (3.2) is a reduced FEct of equation (3.1) if no covariates exists.

The matrix completion estimator

The matrix completion estimator model (MC) aims to complete a matrix with missing values when $D_{it} = 1$. It assumes that the untreated potential outcome — the $N \times T$ matrix $\boldsymbol{y}(0)$ ($\boldsymbol{y}(0) = [y_{it}(0)]_{i=1,2,...,N,t=1,2,...,T}$) can be approximated by a lower-rank $N \times T$ matrix $\boldsymbol{M}$ ($[M_{it}]_{i=1,2...,N,t=1,2...,T}$). The $N \times T$ matrix $\boldsymbol{y}(1)$ ($\boldsymbol{y}(1) = [y_{it}(1)]_{i=1,2,...,N,t=1,2,...,T}$) is the real observations of treated units. If we omit covariates and additive fixed effects for convenience, the MC equation can be written as:

$$y_{it} = \delta_{it} D_{it} + \boldsymbol{M} + \boldsymbol{\varepsilon}, \tag{3.3}$$

where $\boldsymbol{\varepsilon}$ ($[\varepsilon_{it}] = i = 1, 2, ..., N, t = 1, 2, ..., T$) is an $N \times T$ matrix of idiosyncratic errors. MC differs from IFEct in terms of regularizing the singular values from decomposing errors and estimation of counterfactual estimators. Equation (3.2) which omits covariates and additive fixed effects can be expressed to

$$y_{it} = \delta_{it} D_{it} + \boldsymbol{F\Omega} + \boldsymbol{\varepsilon}, \tag{3.4}$$

where $\boldsymbol{F\Omega}$ in equation (3.4) is an $N \times T$ matrix which corresponds to the $N \times T$ matrix $\boldsymbol{M}$ in equation (3.3), $\boldsymbol{F} = [f_1, f_2, ..., f_T]'$ is a $T \times r$ matrix, $\boldsymbol{\Omega} = [\omega_1, \omega_2, ..., \omega_N]'$ is an $N \times r$ matrix, which corresponds to unobserved common factors and factor loadings in IFEct equation (3.2), respectively; $\boldsymbol{F}'\boldsymbol{F}/T = \boldsymbol{I}_r$ and $\boldsymbol{\Omega}'\boldsymbol{\Omega} = diagonal$; $\boldsymbol{\varepsilon}$ is a $N \times T$ matrix. The MC estimates matrix $\boldsymbol{M}$ directly while IFEct estimates both $\boldsymbol{F}$ and $\boldsymbol{\Omega}$ matrices individually.

3.4.2 Difference-in-Differences

In the same spirit with synthetic control method, DiD evaluate treatment effects by comparing treated group and control group. In this sample, there are 3 ETFs joined margin trading and short selling on January 2019, these 3 ETFs acquired the qualification on April 2019, and the rest 3 ETFs joined on July 2019. Thus, I also use a time-varying DiD as a comparison:[3]

$$y_{it} = \beta_0 + \beta_1 treat_{it} + \beta_2 time_{it} + \beta_3 treat_{it} * time_{it} + \varepsilon_{it}, \tag{3.5}$$

where y_{it} is the outcome viable, i refers to ETF, and t refers to month. The $treat_{it}$ and $time_{it}$ is group dummy variable and time dummy variable, respectively. The $treat_{it}$ equals to 1 if ETF_{it} comes from the treat group; $treat_{it}$ equals to 0 when ETF_{it} comes from the control group. Similarly, the $time_{it}$ reflects the policy reform time. The month which ETF_{it} has margin trading and short selling qualification and the later months given $time_{it} = 1$, and the rest of months without margin trading and short selling qualification given $time_{it} = 0$. The interactive term $treat_{it} * time_{it}$ equals to 1 only if both $treat_{it}$ and $time_{it}$ equals to 1. The constant coefficient β_0 reflects influential factors before reform in control group, β_1 reflects the difference between treat group and control group, β_2 reflects common shocks via time, and the most important coefficient β_3 shows treatment effects.

[3]It can be expressed to the same form as equation (3.2), which is specific case of FEct.

For ETFs in the control group ($treat_{it} = 0$), the market quality before and after acquiring margin trading and short selling qualification can be written as:

$$y_{it} = \begin{cases} \beta_0, & \text{if } time_{it} = 0 \\ \beta_0 + \beta_2, & \text{if } time_{it} = 1 \end{cases} \tag{3.6}$$

It is clear to see that ETFs without entering margin trading and short selling list have a change of $\beta_0 + \beta_2 - \beta_0 = \beta_2$ in the post-treatment time.

For ETFs in the treat group ($treat_{it} = 1$), the market quality before and after acquiring margin trading and short selling qualification can be written as:

$$y_{it} = \begin{cases} \beta_0 + \beta_1, & \text{if } time_{it} = 0 \\ \beta_0 + \beta_1 + \beta_2 + \beta_3, & \text{if } time_{it} = 1 \end{cases} \tag{3.7}$$

The changing of market quality in treat group is captured by $\beta_2 + \beta_3$. Thus, the "pure" treatment effect is $\beta_2 + \beta_3 - \beta_2 = \beta_3$, which is the interactive coefficient in equation (3.5). If margin trading and short selling qualification has positive impact on ETFs market quality, β_3 should be positive.

DiD method controls other possible influential factors by acquiring the common influence (β_2) in control equation (3.6), and subtracts it in treat equation (3.7). This idea bases on an assumption that treat group and control group have common trend. In other words, if the difference between treat group and control group is not fixed in pre-treatment time, biased policy evaluation will occur. Another important assumption is that the selection of treat units is randomly. Obviously, we will face the endogenous problem if liquidity, price efficiency, volatility and return determinate whether an ETF can enter the margin trading and short selling list. The later sections will explain why bias occur in my sample by DiD method.

3.4.3 Estimation of Average Treatment Effect

This paper starts from FEct model without time-varying confounders, then considers IFEct and MC after failing diagnostic tests of FEct. All treated units have no treatment reversal but enter into treatment period in different points in the following empirical analysis. Also, the ETFs in the control group (N_{co}), never enter margin trading and short selling pilot list in the sample period. Let $ETF_i \in N_{tr}$, ETF_i stays out of margin trading and short selling list in periods $1, ..., T_{i0}$, where T_{i0} is the point in which the ETF_i switches from a control-treatment state to an active-treatment state. My main interest is the average treatment effect (ATT) of margin trading and short selling on Chinese ETFs (when $t > T_{i0}$).

$$ATT_t = \frac{\sum_{i,D_{it}}[y_{it}(1) - \hat{y}_{it}(0)]}{\sum_i D_{it}} = \frac{\sum_{i,D_{it}} \hat{\delta}_{it}}{\sum_i D_{it}} \tag{3.8}$$

In the post-treatment periods, $y_{it}(1)$ refers to real observations of treated ETFs, while $y_{it}(0)$ is only observable for controlled ETFs. In order to estimate ATT_t, the essential step is estimating $y_{it}(0), i \in N_{tr}$ and get $\hat{y}_{it}(0)$. In other words, we need to generate counterfactual outcomes in post-treatment periods by assuming treated units have not joint the margin trading and short selling program. Generalized synthetic control method (Xu, 2017) and counterfactual method (Liu et al., 2020) regard causal inference problem as forecasting missing data and construct counterfactual estimators for every treated units in post-treatment period. Because FEct is a reduced form of IFEct and MC if there are no common factors ($r = 0$), the following illustration shows IFEct and MC estimation process, respectively.

In order to acquire the estimated treatment effect $\hat{\delta}_{it} = y_{it}(1) - \hat{y}_{it}(0)$, there are three steps to get $\hat{y}_{it}(0)$ (Xu, 2017). Firstly, in order to solve IFEct equation (3.4), we need to solve the following minimization problem:

$$\begin{aligned} (\hat{\beta}, \hat{\boldsymbol{F}}, \hat{\boldsymbol{\Omega}}) &= \arg\min \sum_{i=1}^{N_{co}} (y_{it} - x_{it}\tilde{\beta} - \tilde{\boldsymbol{F}}\tilde{\omega}_i)'(y_{it} - x_{it}\tilde{\beta} - \tilde{\boldsymbol{F}}\tilde{\omega}_i), \\ s.t \qquad & \tilde{\boldsymbol{F}}'\tilde{\boldsymbol{F}}/T = \boldsymbol{I_r} \ and \ \tilde{\boldsymbol{\Omega}}'\tilde{\boldsymbol{\Omega}} = diagonal \end{aligned} \tag{3.9}$$

where $\hat{\beta}$ is a $(p \times 1)$ vector, $\hat{\boldsymbol{F}}$ is a $(T \times r)$ factor matrix, $\hat{\boldsymbol{\Omega}}$ is a $(N_{co} \times r)$ factor loadings matrix, and all of them are obtained from control group only; $\hat{\beta} = [\hat{\beta}_1, \hat{\beta}_2, ..., \hat{\beta}_p]'$, $\hat{\boldsymbol{F}} = [\hat{f}_1, \hat{f}_2, ..., \hat{f}_T]'$, $\hat{f}_t = [\hat{f}_{1t}, \hat{f}_{2t}, ..., \hat{f}_{rt}]'$, $\hat{\boldsymbol{\Omega}} = [\hat{\omega}_1, \hat{\omega}_2, ..., \hat{\omega}_{N_{co}}]'$, $\hat{\omega}_i = [\hat{\omega}_{1i}, \hat{\omega}_{2i}, ..., \hat{\omega}_{ir}]'$. Bai (2009) explains that $\boldsymbol{F\Omega}' = \boldsymbol{FAA^{-1}\Omega}'$ for an arbitrage $r \times r$ invertible $\boldsymbol{A}$, which needs r^2 restrictions for identification. The normalization $\boldsymbol{F}'\boldsymbol{F}/T = \boldsymbol{I}_r$ yields $\frac{r(r+1)}{2}$ restrictions and $\boldsymbol{\Omega}'\boldsymbol{\Omega}/T = diagonal$ yields $\frac{r(r-1)}{2}$ restrictions. They jointly determine unique $\boldsymbol{\Omega}$ and $\boldsymbol{F}$.

Secondly, we need to calculate the $\hat{\omega_i}$ by pre-treatment data:

$$\hat{\omega_i} = \arg\min(y_{it} - x_{it}\hat{\beta} - \hat{\boldsymbol{F}}\tilde{\omega_i})'(y_{it} - x_{it}\hat{\beta} - \hat{\boldsymbol{F}}\tilde{\omega_i}), \tag{3.10}$$

where $\hat{\beta}$ and $\hat{\boldsymbol{F}}$ are obtained from equation (3.10).

Finally, we can estimate the post-treatment counterfactuals:

$$\hat{y_{it}}(0) = x'_{it}\hat{\beta} + \hat{\omega_i}'\hat{f_t}, \tag{3.11}$$

where x_{it} is a $(p \times 1)$ vector of covariates, $\hat{\beta}$ is a $(p \times 1)$ vector of calculated parameters, $\hat{\omega_i}$ is an $(r \times 1)$ vector of estimated factor loadings, $\hat{f_t}$ is an $(r \times 1)$ vector of estimated common factors.

The FEct can be a special case of IFEct and the estimation strategy is similar in these three steps. Let $f_{1t} = 1$, $\omega_{i2} = 1$, $f_{2t} = \lambda_t$, $\omega_{i1} = \mu_i$, then the factor component $(\hat{\omega_i}'\hat{f_t} = \hat{\omega_{i1}}'\hat{f_{1t}} + \hat{\omega_{i2}}'\hat{f_{2t}} + ... + \hat{\omega_{ir}}'\hat{f_{rt}})$ of IFEct equation (3.11) can be written as $\hat{\omega_{i1}}'\hat{f_{1t}} + \hat{\omega_{i2}}'\hat{f_{2t}} = \hat{\mu_i} + \hat{\lambda_t}$. Therefore, the estimated counterfactuals of FEct equation (3.1) is

$$\hat{y_{it}}(0) = x'_{it}\hat{\beta} + \hat{\mu_i} + \hat{\lambda_t}, \tag{3.12}$$

where x_{it} is a $(p \times 1)$ vector of covariates, $\hat{\beta}$ is a $(p \times 1)$ vector of calculated parameters, $\hat{\mu_i}$ and $\hat{\lambda_t}$ is estimated additive unit and time fixed effect, respectively.

In terms of the MC estimation strategy, we assume non-treated units follow MC equation (3.3) and calculate the minimization equation:

$$\hat{\boldsymbol{M}} = \arg\min[\sum_{i=1}^{N_{co}} \frac{(y_{it} - M_{it})^2}{N_{co}} + \theta\|\boldsymbol{M}\|], \tag{3.13}$$

where θ is a tuning parameter and $\|\boldsymbol{M}\|$ is the chosen nuclear norm (Athey et al., 2021) of the $N \times T$ matrix $\boldsymbol{M}$.

3.4.4 Diagnostic Tests

An important feature of the synthetic control method and its extensions is the inferential procedures based on diagnostic studies, such as placebo test. Abadie et al. (2010) compare the ratio of the post and pre-treatment mean squared prediction error (MSPE) of synthetic control estimator, and consider whether the ratio of the real treated unit is significantly larger than the prediction errors of non-treated units. The large MSPE value in pre-treatment time indicates poor synthetic control fitting; thus, the predicted effect gap in post-treatment cannot reliably reflect real treatment effect. Abadie et al. (2010) discard states which excess 20 times the MSPE of the treated state—California. This analysis has a subjective problem since researchers need to set a unique MSPE value to delete poor-fitting states in pre-treatment periods, and there is no clear rule to reject the null hypothesis of no effect whatsoever. A recent study (Firpo and Possebom, 2018) extends the inference procedure of the synthetic control method and proposes a way to calculate confidence sets. Liu et al. (2020) further propose equivalence test and placebo test with p value. The idea of the placebo test proposed by Liu et al. (2020) assumes that the treatment periods start earlier than its actual treatment time T_0 and use the same estimators to generate estimates of ATT. This brief test differs from the placebo test of Abadie et al. (2010) and Firpo and Possebom (2018) which does not require to construct a series of placebo tests by applying iterative synthetic control operations.

I follow Liu et al. (2020) to test the significance of treatment effect and estimate the residual averages ATT_s of treated units in each pre-treated period by using observations in pre-treatment:

$$ATT_s = \sum_{i \in N_t} \hat{e}_{is}/N_t, \qquad D_{is} = 0 \; and \; s \leq T_0. \tag{3.14}$$

T_0 represents the total number of pre-treated periods, and $D_{is} = 0$ means non-treatment state. Given the zero residual means null hypothesis ($H_0 : ATT_s = 0, \forall s \leq T_0$), we can construct the F statistics:

$$F = \frac{\sum_{i \in N_t} \sum_{t=1}^{T_0} (\hat{e}_{is}^2 - (\hat{e}_{is} - ATT_s^2))/T_o}{\sum_{s \in N_t} \sum_{s=1}^{T_0} (\hat{e}_{is} - ATT_s)^2/(N_t \times T_0 - T_0)} \tag{3.15}$$

Liu et al. (2020) propose a variant test by the null hypothesis:

$$ATT_s < -\theta_2 \ or \ ATT_s > \theta_1, \qquad \forall s \leq T_0, \tag{3.16}$$

where θ_1 and θ_2 are pre-specified parameters. I follow Hartman and Hidalgo (2018) and set $\theta_1 = \theta_2 = 0.36\sigma_\varepsilon$; σ_ε is the standard deviation of residuals in non-treated group. If the residuals of pre-treated periods fall whin the equivalence bound ($[-\theta_2, \theta_1]$), we can reject the null hypothesis and accept the alternative hypothesis of $-\theta_2 \leq ATT_s \leq \theta_1$ for any $s \leq T_0$. In addition, set a minimal bound to be the smallest symmetric bound which we cannot reject the null hypothesis under equivalent test, where the minimum bound depends on the absolute value of largest confidence intervals of ATT_s in the pre-treatment periods. If the treatment effect is significant, we expect the pre-treatment residuals fall within the equivalence bound, and the minimum bound also lay inside of the equivalence bound.

For placebo test, we can assume that the treatment time of unit i starts k period(s) earlier than its actual treatment starts time T_0. Donate the assumed pre-treatment periods T_0', where $T_0' = T_0 - k_i$. Then we use the same counterfactual estimator to obtain ATT_s for $s \in T_0'$. If the ATT_s estimate is significantly undistinguished with zero (when zero residual means do not hold), we accept the alternative hypothesis of no time-varying confounder ($r = 0$). Otherwise, the time-varying confounder exists if ATT_s estimate closes to zero. This placebo test is very sensitive to k, especially when treatment reversal happens frequently. Researchers might find that k is hard to choice perfectly. Besides, if treated units and their pre-treatment periods are too small, or the k is selected too large, this placebo test will become less valid as fewer pre-treatment observations available. The equivalence test also has the problem of parameter selecting, i.e., if θ_1 and θ_2 are too lenient to the corresponding effect size, the equivalence test might be too easy to pass.

3.5 Empirical Results

This section presents the empirical results of three different models and equivalence tests, investigating the effects of margin trading and short selling qualification on

ETFs liquidity, price efficiency and price volatility in the Chinese market. Most relevant studies use the DiD method and Propensity Score Matching (PSM) method, which are mainly based on individual-level data rather than panel data. There are two majority limitations. First, both methods face the problem of subjective selection. Moreover, it is hard to summarize a general policy effect if different stocks or funds have different policy effects. Synthetic control method addresses the self-selection problem, but it is widely used in policy evaluation with low frequency and relatively small sample. I find that Chinese ETFs monthly sample (2016 to 2019) satisfies synthetic control data requirements and it is possible to evaluate more updated margin trading and short selling policy effects on Chinese ETFs in another sample periods.

3.5.1 Counterfactual Estimation Results

From the results of Table 3.2, we can see that the coefficient of margin trading and short selling is positive and significant in all regressions, while the treatment coefficient of spread is negative and insignificant in all regressions. Neither of the diagnostic tests is passed. The placebo test is very sensitive with the selection of assumed earlier starting point S, and test results might vary with different S. Besides, in the treatment reversal scenario, the placebo test ignores unobserved factors which appear only periodically and become more sensitive with the assumption of starting S stages earlier. The equivalence test may suffer from over-fitting and wrong model specification. As we can set equivalence bound $[-\theta_2, \theta_1]$ subjectively, and it may cause bias estimate as well—the equivalence test becomes to easy to pass.

In Figure 3.7(a) and Figure 3.7(b), ETFs trading volume and turnover have an obvious positive treatment effect. However, both of them have quite wide confidence intervals in the post-treatment periods either applying MC or IFEct methods. In the first and second row of Figure 3.7(a), we can see the Wald test p-value of trading volume in the left top corner is smaller than 0.05. Thus, we can reject the null hypothesis that pre-treatment residuals averages over time are jointly close to zero. In other words, ETFs trading volume increased significantly before acquiring margin trading and short selling qualification generally. It can partly explain why equivalence

Table 3.2: Main Results of ETFs Liquidity

	Trading volume			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	30,598,616***	30,598,616***	30,598,616***	28,692,938***
	(11,833,794)	(11,589,868)	(11,840,800)	(3,219,990)
Volatility	34,407,192***	34,407,192***	34,407,192***	2,186,115
	(12,977,830)	(11,953,404)	(14,250,021)	(2,360,298)
Efficiency	-5,656,118***	-5,656,118***	-5,656,118***	-1,066,550
	(2,995,867)	(2,781,629)	(2,966,620)	(1,046,080)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	PASS	PASS	PASS	N/A
r/lambda.norm	N/A	1	0	1
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51
	Turnover			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	0.0327***	0.0320**	0.0327**	0.0333***
	(0.0209)	(0.0205)	(0.0190)	(0.0031)
Volatility	0.1340***	0.1212***	0.1340***	0.0907***
	(0.0638)	(0.0401)	(0.0635)	(0.0352)
Efficiency	-0.0102	-0.0179*	-0.0102	-0.0049
	(0.0151)	(0.0099)	(0.0138)	(0.0162)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	FAIL	FAIL	FAIL	N/A
r/lambda.norm	N/A	0.1778	0	0
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51
	Spread			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	-0.0021	-0.0015	-0.0021	-0.0007
	(0.0020)	(0.0017)	(0.0020)	(0.0037)
Volatility	0.2294***	0.2257***	0.2294***	0.1954***
	(0.0632)	(0.0534)	(0.0621)	(0.0318)
Efficiency	0.15639***	0.1448***	0.1564***	0.1540***
	(0.0355)	(0.0265)	(0.0353)	(0.0183)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	FAIL	FAIL	FAIL	N/A
r/lambda.norm	N/A	0.1778	0	2
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51

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

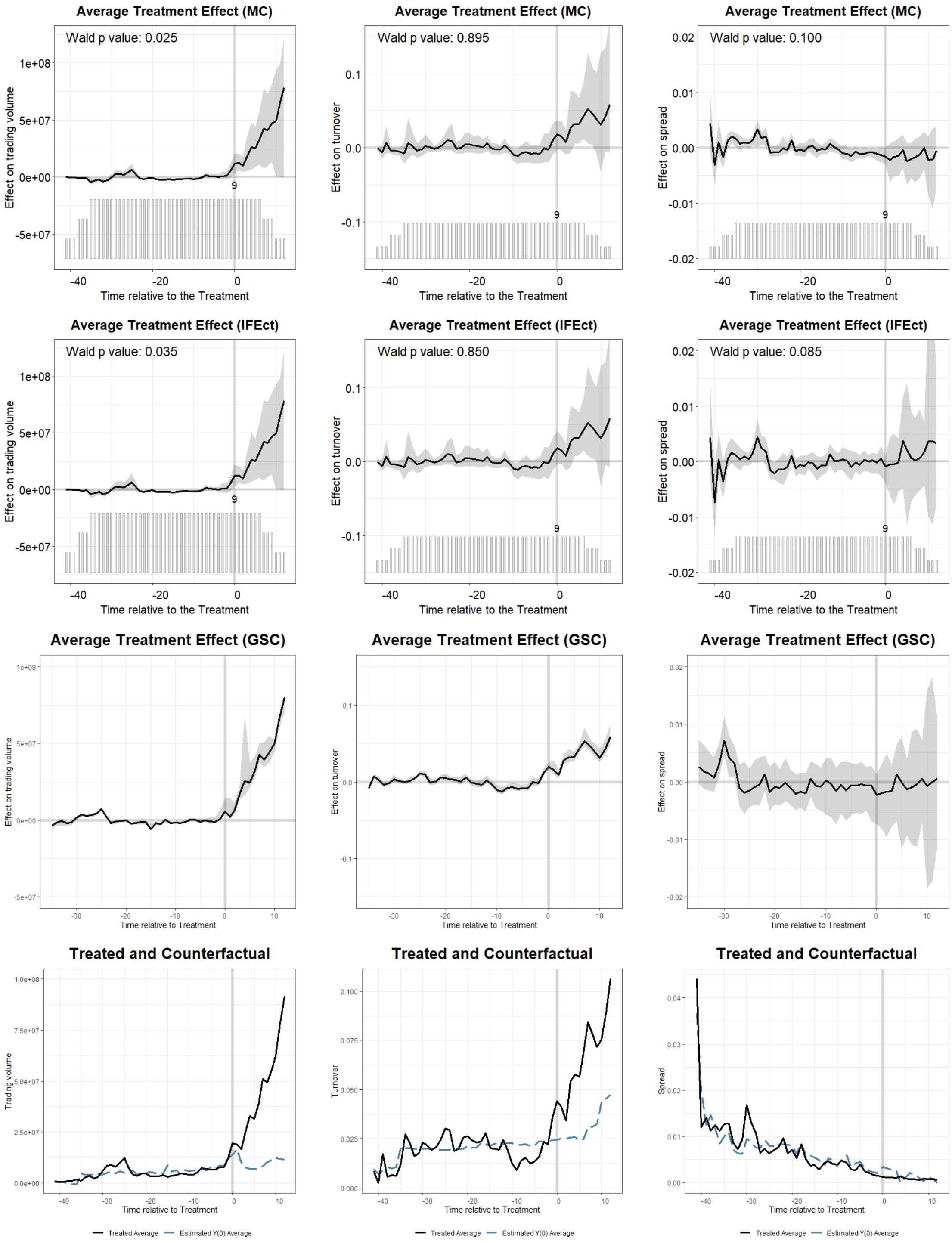
tests failed in Table 3.2.

However, the Wald test p-value of turnover (Figure 3.7(b)) is larger than 0.05 with MC method (95% confidence interval), which means its pre-treatment residuals averagely close to zero and there is no strong pre-trend. Turnover cannot pass the equivalence test with the MC method, which confirms that good model fitness in pre-treatment periods is not a guarantee of correct model specification. Note that the GSC method almost estimates the same treatment effect on ETFs trading volume and turnover as MC and IFEc methods. Besides, its confidence intervals of the ATT estimates in the post-treatment periods are much narrower. The main reason is that GSC method releases the constant treatment restriction. If the treatment effect is heterogeneous ($\delta_{it} \neq \delta$), IFEct will leads to bias due to constant treatment assumption. In this case, the GSC method is superior to other approaches.

The suggested ETFs liquidity indicator (Fong et al., 2017)—spread shows no significant treatment effect by MC and GSC methods. Figure 3.7(c) shows a strong pre-trend in non-treatment periods by IFEct method. GSC method achieves better model fitness in pre-treatment periods than IFEct method, but it has the lowest estimation precision as confidence intervals of GSC are wider than any others. In the case of spread, GSC is not the superior approach. One reason is that MC can improve their model precision by using pre-treatment values of treatment units and controlled units, while GSC only uses observations in the control group. Compares with GSC, IFEct shows poorer fitness in the pre-treatment periods due to constant treatment effect assumption, and it has better estimation precision because the treatment group is larger.

Nevertheless, the mixed treatment results tell us that 1) spread is not an ideal liquidity proxy in my sample with synthetic control application, 2) ETFs trading volume and turnover increase with the introduction of margin trading and short selling, but 3) failed diagnostic tests indicate an advanced or pre-selection of treated ETFs.

The most direct way to measure an ETF price efficiency is comparing the NAV and its trading price. Table 3.3 shows a positive but insignificant treatment estimation of ETFs price premium, where the sign of coefficient opposites with the hypothesis



(a) Trading Volume (b) Turnover (c) Spread

Figure 3.7: Estimated Average Effect on ETFs Liquidity

of reducing price overvaluation (Miller, 1977). Compare with underlying indexes, treated ETFs have an upward price adjustment after lifting margin trading and short selling bans. Charoenrook and Daouk (2009) explains that if expected returns are lower in free short selling periods, stock prices should increase because of constant future cash flows are expected. Another possible reason is that margin trading effect eliminates short selling effect[4] , thus overprice cannot be fully corrected (Bhojraj et al., 2009). The relaxing of margin trading constraints can exacerbate observed ETFs price premium, while short selling permission eliminates overpricing. These two opposing forces might have an impact on assets prices simultaneously if both leverage activities are allowed.

Table 3.3: Main Results of ETFs Price Efficiency

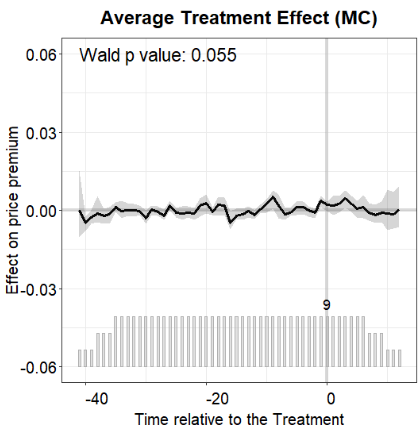
	Price efficiency			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	0.0018	0.0011	0.0018	0.0019
	(0.0022)	(0.0018)	(0.0024)	(0.0028)
Volatility	0.8528***	0.7326***	0.8528***	0.7937***
	(0.1549)	(0.0758)	(0.1583)	(0.0652)
Spread	0.4365***	0.3735***	0.4365***	0.4632***
	(0.1067)	(0.0808)	(0.1117)	(0.0679)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	FAIL	FAIL	FAIL	N/A
Unobserved factors	N/A	0.1778	0	0
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51

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

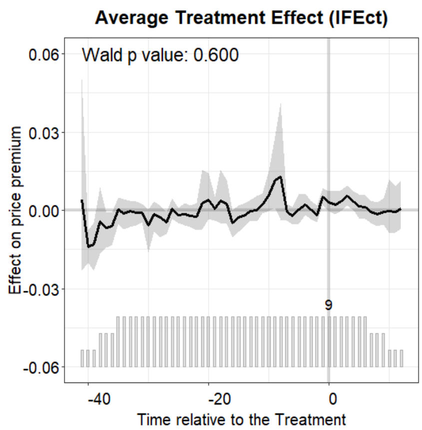
In figure 3.8(a) three methods do not show a significant effect on ETFs premium. MC method fits best among different models, but the pre-trend exist as Wald test p-value is close to zero. The sub-optimal method is GSC, which has smaller bias than IFEct. The estimated average treatment effect of price efficiency fluctuates slightly between −0.01% to 0.01%. Similar to ETFs spread, the price efficiency measurement is sensitive to the market situation. The actual averaged price efficiency of treated ETFs is more than 0.04% at the beginning of 2016, which is around three times as other observed periods. Although the synthetic premium is close to the actual premium in market fluctuation period, the confidence intervals become large.

[4]Bhojraj et al. (2009): "Unfavorable price movements will trigger a margin call that forces traders to close out positions at a loss before the overpricing is fully corrected. Thus, relaxing margin requirements typically allows for more aggressive short selling and reduces the equilibrium level of overpricing."

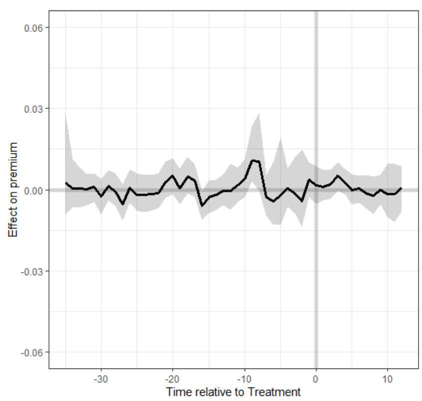
Nevertheless, the results of these three counterfactual estimation models show insignificant price efficiency improvement to the treated ETFs after margin trading and short selling introduction. One of the reasons might be the highly unbalanced amount of margin trading and short selling in the Chinese market. The shortage of short selling security supplement and higher security deposit proportion hit short selling activities. Besides, Chinese Securities Regulatory Commission issues a series of policies to standardize investment operation, such as prohibiting naked short and executing uptick rule[5] which mandates short sellers to hold securities unless price rising. These additional limitations to short sales make short selling activities less active.



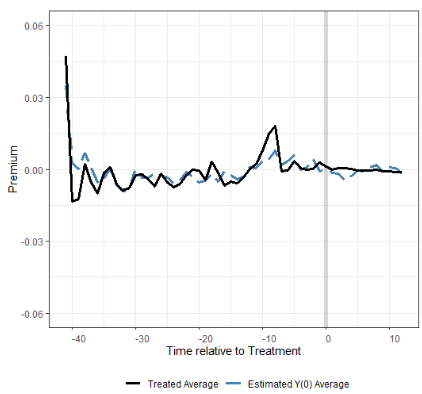
(a)



(b)



(c) Average Treatment Effect (GSC)



(d) Treated and Counterfactual (GSC)

Figure 3.8: Estimated Effect on ETFs Price Efficiency

[5]The Securities Association of China and other four departments jointly issued an announce in April 2015, which allows investors to short sell ETFs lower than the latest transaction price. Nevertheless, stocks still need to obey uptick rule.

The overvaluation hypothesis (Miller, 1977) argues that short sales constraints cause prices overvaluation since stock prices partial reflect valuations of most optimistic investors, while there is no obvious gap between synthetic ETFs premium and actual ETFs premium in this sample. Additionally, I apply the return rate to jointly exam the overvaluation hypothesis. Table 3.4 summarizes regression results and diagnostics tests of ETFs return. The covariates include price volatility and spread. We can see that the IFE model and GSC model have zero common factor and similar results; thus, they have similar estimation with the FE model. These three models have estimated ATT around -0.03 percent with a standard error of 0.03 per cent, while MC counterfactual estimator (-0.0001) is more negligible. The negative return coefficient indicates that investors require a lower rate of return in a more completed market. Margin trading and short selling allow investors to better diversify risks from heterogeneous beliefs.

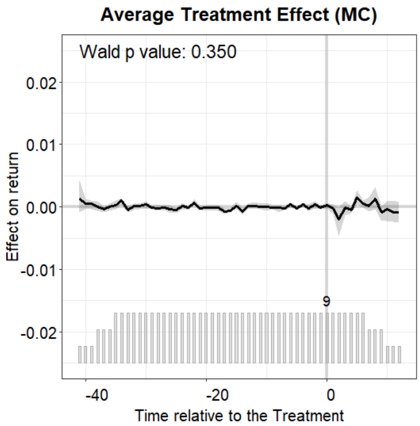
It is not surprising that the equivalence test and placebo test failed due to insignificant treatment estimators. In Figure 3.9, the synthetic ETFs return cannot well fit the actual return of treatment units. At the beginning of the sample periods, ETFs return reaches to the highest point (0.05%) but falls to the lowest point (-0.05%) within three months. After a market adjustment, averaged ETFs return is positive in the most, and the high-low return band shrinks to (±0.025%). From relative flat treatment estimation graph (Figure 3.9(a), 3.9(b), 3.9(c)) and failed diagnostic test, we can deduce that ETFs return changes vary with market situations and treated ETFs do not rise and fall in lockstep in post-treatment time.

Table 3.4: Main Results of ETFs Return

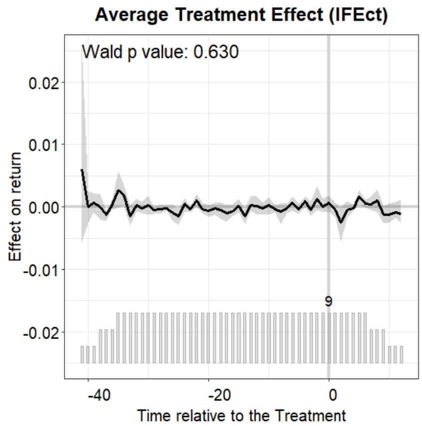
	Return			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	-0.0003***	-0.0001***	-0.0003***	-0.0003***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Volatility	0.0456**	0.0413***	0.0456***	(0.0437)***
	(0.0169)	(0.0108)	(0.0175)	(0.0082)
Spread	0.0301**	0.0190***	0.0301**	0.0265***
	(0.0152)	(0.0078)	0.0148	(0.0070)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	PASS	PASS	PASS	N/A
r/lambda.norm	N/A	0.1778	0	0
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51

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

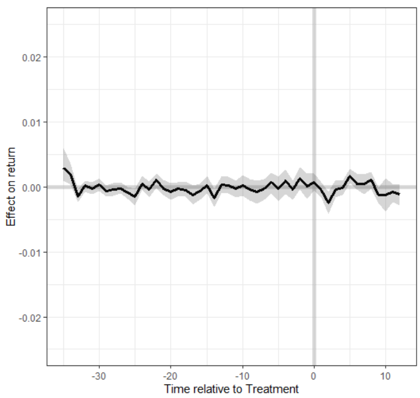
Table 3.5 presents results of ETFs price volatility. The cross-validation of GSC finds



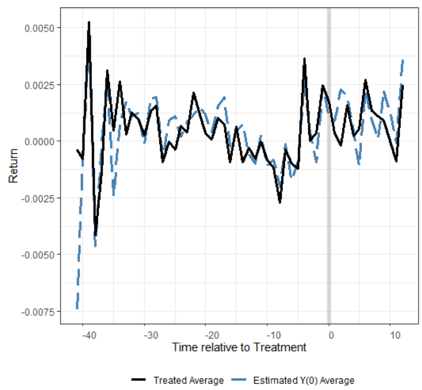
(a)



(b)



(c) Average Treatment Effect (GSC)



(d) Treated and Counterfactual (GSC)

Figure 3.9: Estimated Effect on ETFs Return

two unobserved factors with a statistic significant ATT of -0.48 percent, while the IFEct approach shows zero unobserved factors with an insignificant ATT of -0.18 per cent. Our empirical results report a negative relationship between ETFs volatility and the lifting margin trading and short selling restrictions, but the treatment effect coefficients are very light.

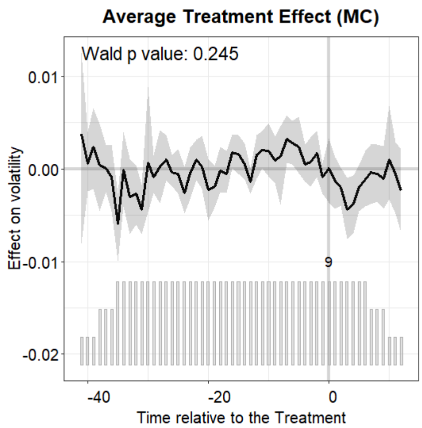
Different treatment estimation models have a similar downward trend after entering the dual introduction program and the treatment effect disappears gradually. The model difference is also shown in Figure 3.10, we can see a wider grey band in the GSC estimation, although the shape of estimated treatment effect graphs is very similar. When the treatment effect is constant, MC and IFEct method is more efficient than GSC since their use of additional observations (pre-treatment values of treated units) to estimate covariate coefficients and factors, while GSC method only applies observations in the control group.

Figure 3.10(d) shows a return to a normal level of volatility around ten months after the dual introduction of margin trading and short selling. In sum, the removal of leverage trading bans on selected ETFs declines volatility on average in the short term, but the effect does not exist in the long term. Moreover, since the margin trading effect and short selling effect are usually viewed as opposite forces, either of those two effects can dominate in this sample. It is hard to distinguish which one causes volatility decline or attributes to the later volatility rebound.

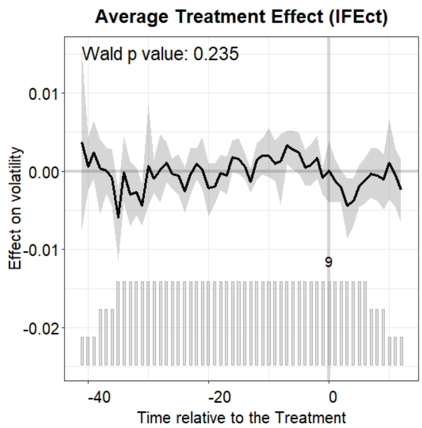
Table 3.5: Main Results of ETFs Price Volatility

	Price volatility			
	FE	MC	IFE	GSC
Margin Trading and Short Selling Qualification	-0.0018**	-0.0018**	-0.0018**	-0.0048**
	(0.0011)	(0.0011)	(0.0013)	(0.0020)
Efficiency	0.2182***	0.2182***	0.2182***	0.2545***
	(0.0259)	(0.0241)	(0.0260)	(0.0181)
Spread	0.1727***	0.1727***	0.1727***	0.1625***
	(0.0467)	(0.0506)	(0.0516)	(0.0366)
Turnover	0.0529***	0.0529***	0.0529***	0.0844***
	(0.0231)	(0.0220)	(0.0226)	(0.0222)
Equivalence Test	FAIL	FAIL	FAIL	N/A
Placebo Test	FAIL	FAIL	FAIL	N/A
r/lambda.norm	N/A	1	0	2
Observations	2880	2880	2880	2880
Treated ETFs	9	9	9	9
Control ETFS	51	51	51	51

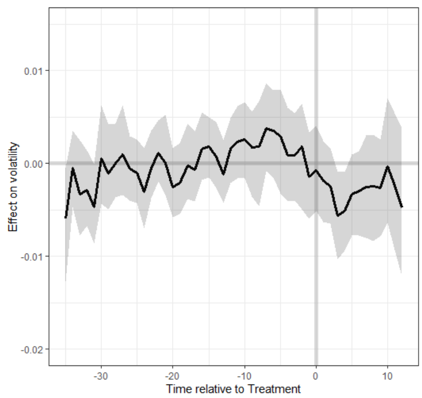
* p<0.10, ** p<0.05, *** p<0.01



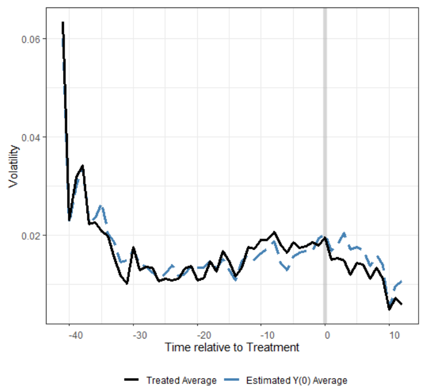
(a)



(b)



(c) Average Treatment Effect (GSC)



(d) Treated and Counterfactual (GSC)

Figure 3.10: Estimated Effect on ETFs Volatility

3.5.2 Difference-in-Differences Results

There are two important prerequisites of DiD method. The first precondition is random treat units selection. The second precondition is that treat units and control units have common trend in pre-treatment time. If market quality proxies such as liquidity, price efficiency, volatility and return can determine whether an ETF can acquire margin trading and short selling qualification, DiD method will present biased evaluation due to endogenous problem. For example, results might report liquidity improvement after treatment, but the real reason is ETFs in treat group already have much higher liquidity than ETFs in control group.

From the official report in Shainghai Exchange and Shenzhen Exchange, ETFs with margin trading and short selling qualification should satisfy certain conditions. In the early stage, large size, early published and high liquidity ETFs are more likely acquiring margin trading and short selling qualification. Later, there are more niche, small size or newly published ETFs enter margin trading and short selling list. The requirements adjust every year before 2016 but standards tend to be unified after 2015, which include 1) recorded trading days excess 5 days, 2) the latest 5-day average asset size is not less than 5 billion yuan, and 3) the total holder number is not less than 2000 accounts. Due to the limitation of data frequency and data availability, Figure 3.11 roughly compares the number of eligible ETFs and listed ETFs from 2018 to 2019. It indicates that not every ETF reaches these requirements will enter margin trading and short selling list soon or later.

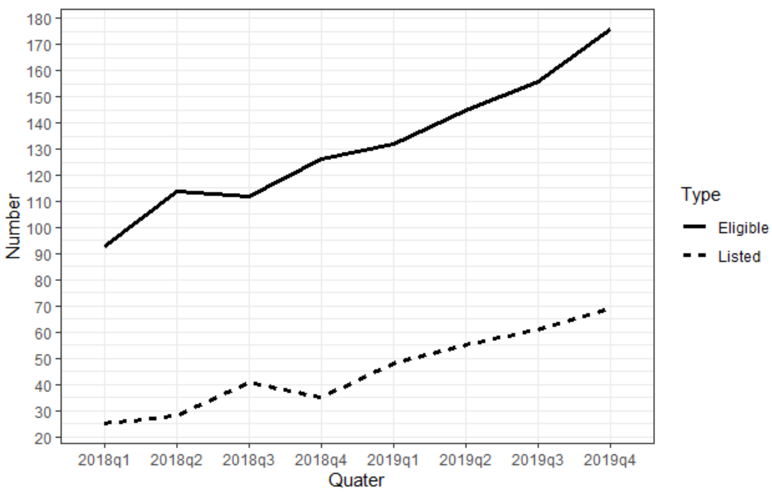


Figure 3.11: Eligible ETFs and Listed ETFs

Further, I uses logistics regression to examine whether market quality proxies are determinate factors for acquiring margin trading and short selling qualification. The sub sample includes the same treated ETFs and control ETFs but excludes post-treatment time. Table 3.6 reports logistics regression results, where the independent variable is whether an ETF has margin trading and short selling qualification and market value is the control variable in all regressions. Regression 1 to 3 of Table 3.6 show that all liquidity measurements are significant in 1 percent confidence level. ETFs with higher liquidity have higher possibility to be selected into margin trading and short selling list. These results consist with counterfactual estimation findings in the previous section, where strong pre-trend exists and placebo tests failed. But, coefficients of the last three columns in Table 3.6 are not significant, which means market quality proxies such as price efficiency, volatility and return are not determinate factors of ETFs margin trading and short selling selection.

Table 3.6: Logistic Regression

	reg(1)	reg(2)	reg(3)	reg(4)	reg(5)	reg(6)
Trading Volume	0.000***					
	(-8.583)					
Turnover		47.396***				
		(-8.819)				
Spread			-44.541***			
			(-5.420)			
Efficiency				0.669		
				(-0.18)		
Volatility					-4.083	
					(-0.672)	
Return						29.642
						(-1.455)
Market Value	-0.000	0.000***	0.000***	0.000***	0.000***	0.000***
	(-1.398)	-7.675	-7.528	-9.172	-8.86	-9.165
_cons	-2.133***	-2.456***	-1.642***	-2.137***	-2.061***	-2.135***
	(-28.344)	(-28.029)	(-14.957)	(-27.925)	(-15.168)	(-27.919)
Pseudo R-squared	0.16	0.14	0.09	0.07	0.07	0.07
Observations	2160	2160	2160	2160	2160	2160

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

The next step is to check whether common trend is satisfied according to the second precondition of DiD. Figure 3.12 shows the average trading volume, turnover, spread, price efficiency, volatility and return between control group and treat group. As ETFs in treat group acquire margin trading and short selling qualification in January, April and July, Figure 3.12 plots treat groups by different starting months and plots control ETFs with whole sample period. It is clear that trading volume and turnover do not show common trend between control group and treat group. ETFs which start margin trading and short selling on January have much higher and more fluctuate trend about trading volume and turnover rate than control group. The rest treat groups have close trend with control group, but their trading volume and turnover rate increased dramatically around one year before real treatment time. Similarly, spread and price efficiency dose not satisfy common trend assumption. The violation of common trend assumption will lead to biased treatment effect evaluation by DiD method.

Figure 3.12: Common Trend Comparison

Table 3.7: Effects on ETFs Market Quality

	Trading volume reg (1)	Turnover reg (2)	Spread reg (3)	Price Efficiency reg (4)	Volatility reg (5)	Return reg (6)
Panel A: No controls						
Margin Trading and Short Selling Qualification	29,228,946.802***	0.032	-0.002	0.000	-0.000	-0.000
	(10,828,666.495)	(0.020)	(0.002)	(0.001)	(0.001)	(0.000)
R-squared	0.35	0.16	0.14	0.12	0.42	0.56
Observations	2880	2880	2880	2880	2880	2880
Panel B: With controls						
Margin Trading and Short Selling Qualification	29,278,928.988***	0.032	-0.002	0.002	-0.001	-0.000
	(10,800,223.281)	(0.020)	(0.002)	(0.002)	(0.001)	(0.000)
Volatility	85,861,715.152**	0.172**	0.237***	0.847***		0.047***
	(37,627,092.146)	(0.066)	(0.064)	(0.161)		(0.017)
Price Efficiency	-20,460,000	-0.021	0.154***	0.426***	0.326***	0.028*
	(9,662,686.899)	(0.014)	(0.034)	(0.106)	(0.059)	(0.016)
Spread						0.028*
				0.426***		(0.016)
Turnover				(0.106)	0.041*	
					(0.022)	
R-squared	0.36	0.17	0.3	0.39	0.5	0.58
Observations	2880	2880	2880	2880	2880	2880

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

The Table 3.7 results report treatment effects by DiD method, which indicates that margin trading and short selling substantially increased trading volume of ETFs. However, another market quality measurements are insignificant. Compare with estimated treatment effect with generalized synthetic control method, DiD method overvalued the positive impact on trading volume.

3.5.3 Discussions

It is also important to understand the potential benefits of prohibiting or re-introducing margin trading and short selling bans. The short selling ban excludes pessimistic investors and then buyers have to trade stocks at artificially high prices, which pretends market value decreasing further and panic selling in some extent during financial crisis. For example, US Securities and Exchange Commission implemented the short selling ban in stock market during the financial crisis of 2008. Harris et al. (2014) find that the temporary short selling ban showed positive effects on stabilizing market prices. Charoenrook and Daouk (2009) report data from 111 countries and state that short selling and put option trading regulations is possibly decreasing aggregate stock return volatility and increasing liquidity, but collectively market quality is enhanced after permitting short selling.

On the one hand, emerging markets are less efficient than developed markets and commonly impose various trading restrictions such as daily price limits, trading suspension rules, uptick rule, market circuit breaker, margin trading and short selling limitation to stabilize financial market, and lifting trading restrictions may has unintended effects. Some empirical studies (Callen and Fang, 2015; Ni and Zhu, 2016) find that short selling is linked with agency problems about managerial bad news hoarding behaviours, which suggests future stock price crash risk for firms with weak external monitoring, high level of information asymmetry. Ni and Yin (2020) state that emerging markets usually have weak investors protection and find that short selling can induce companies to give up profitable but risky projects and loss values. Meng et al. (2020) find that the Chinese short selling deregulation has negative effect on shortable firms in the aspects of the increased negative media coverage possibility, costly external financing, and the difficulty of finding new external capital.

On the other hand, removing the margin trading and short selling bans on a list of ETFs may serve as the evidence that the China Securities Regulatory Commission has successfully improved market efficiency. Furthermore, there is space for relaxing trading restrictions on other assets because different markets interact with each other. Hu et al. (2020) argue that stringent regulations in China such as high margin requirements, low position limit and short selling restrictions in equity markets increase trading costs and decline market liquidity significantly in futures market. Harris et al. (2014) find the cross-sectional link between stock market and option market and suggest that option markets provides a mechanism for traders to circumnavigate the ban in 2008 financial turmoil.

3.6 Conclusion

This chapter seeks to understand whether the recent introduction of margin trading and short selling in the Chinese equity market significantly affects the treated ETFs liquidity, price efficiency, and volatility. The results showed that trading volume treated ETFs increased significantly when the restriction of leverage trading lifted in 2019. The price efficiency of treated ETFs did not show an expected improvement. I observed a decline in return and volatility at the beginning of post-treatment periods. This indicated that leveraged market participants require a lower expected return in a more integrated and stable market to diversify risks better. Neither return nor volatility showed a persistent treatment effect. It is unclear whether margin trading effects or short selling effects dominate in our sample periods. None of these variables passed placebo test or equivalence test, which indicated the existence of pre-trend and no randomization.

Appendix A

Table 3.A1: Control Units

Ticker	Launch date	Tracking index	Market
159906	21dec2010	Shenzhen composite index grew 40	Shenzhen
159907	03jun2011	Small board 300 index	Shenzhen
159909	27jun2011	Shenzhen electronic information media industry 50 index	Shenzhen
159910	01aug2011	Shenzhen fundamental 120 index	Shenzhen
159911	02sep2011	Shenzhen Private Sector index	Shenzhen
159912	16sep2011	Shenzhen 300 price	Shenzhen
159913	22sep2011	Shenzhen 300 value index	Shenzhen
159916	08sep2011	Shenzhen fundamental 60 index	Shenzhen
159918	22mar2012	SME board 400 index	Shenzhen
159923	07feb2013	CSI 100 index	Shenzhen
159929	23aug2013	Chinese health care index	Shenzhen
159920	23aug2013	CSI new energy index	Shenzhen
159931	23aug2013	CSI Financials index	Shenzhen
159932	12sep2013	CSI 500 Shenzhen market index	Shenzhen
159934	29nov2013	Gold 9999	Shenzhen
159935	26dec2013	CSI 500 index	Shenzhen
159936	24oct2003	All share consumer discretionary index	Shenzhen
159940	23mar2015	CSI all share financials Index	Shenzhen
159941	10jun2015	NASDAQ 100 index	Shenzhen
159943	05jun2015	SZSE component index	Shenzhen
159944	25jun2015	CSI all share materials index	Shenzhen
159945	25jun2015	CSI all share energy index	Shenzhen
510020	29dec2009	SSE mega-cap index	Shanghai
510030	23apr2010	SSE 180 Value	Shanghai
510060	30dec2004	SSE central state-owned enterprises 50 index	Shanghai
510070	08aug2010	SSE private-owned enterprises 50 index	Shanghai
510090	28may2010	SSE social responsibility index	Shanghai
510110	19sep2010	SSE cyclical industry index	Shanghai
510120	22apr2011	non-cyclical industry SSE Mid-Cap	Shanghai
510130	29mar2010	SSE mid-cap	Shanghai
510150	08dec2010	SSE consumption 80 index	Shanghai
510170	26nov2010	SSE commodity index	Shanghai
510190	18nov2010	SSE leading enterprise index	Shanghai
510210	30jan2011	SSE composite index	Shanghai
510220	26jan2011	SSE mid-small cap index	Shanghai
510270	16jun2011	SSE state-owned enterprises 100 index	Shanghai
510290	16sep2011	SSE 380 index	Shanghai
510360	20aug2015	CSI 300 index	Shanghai
510410	10apr2012	SSE natural resource index	Shanghai
510430	23aug2012	SSE 50 equal weight index	Shanghai
510440	24aug2012	CSI 500 index	Shanghai
510560	29may2015	CSI small cap 500 index	Shanghai
510580	27aug2015	CSI 500 index	Shanghai
510630	28mar2013	SSE consumer staples sector index	Shanghai
510650	28mar2013	SSE financials sector index	Shanghai
510660	28mar2013	SSE health care sector index	Shanghai
510710	27may2015	SSE 50 index	Shanghai
512010	23sep2013	CSI300 health care index	Shanghai
512120	04dec2013	CSI medican segmentation index	Shanghai
512220	18jul2014	CSI TMT 150 index	Shanghai
512300	30oct2014	CSI 500 medical index	Shanghai
512310	08apr2015	CSI 500 industry index	Shanghai
512340	16apr2015	CSI 500 raw material index	Shanghai
512510	13may2015	CSI 500 index	Shanghai
512600	13jun2014	Core consumption index	Shanghai
512610	13jun2014	CSI health care index	Shanghai
512640	20jun2014	CSI financials index	Shanghai
513600	23dec2014	Hangseng index	Shanghai

Appendix B

Figure 3.B1: Diagnostic Tests of Trading Volume

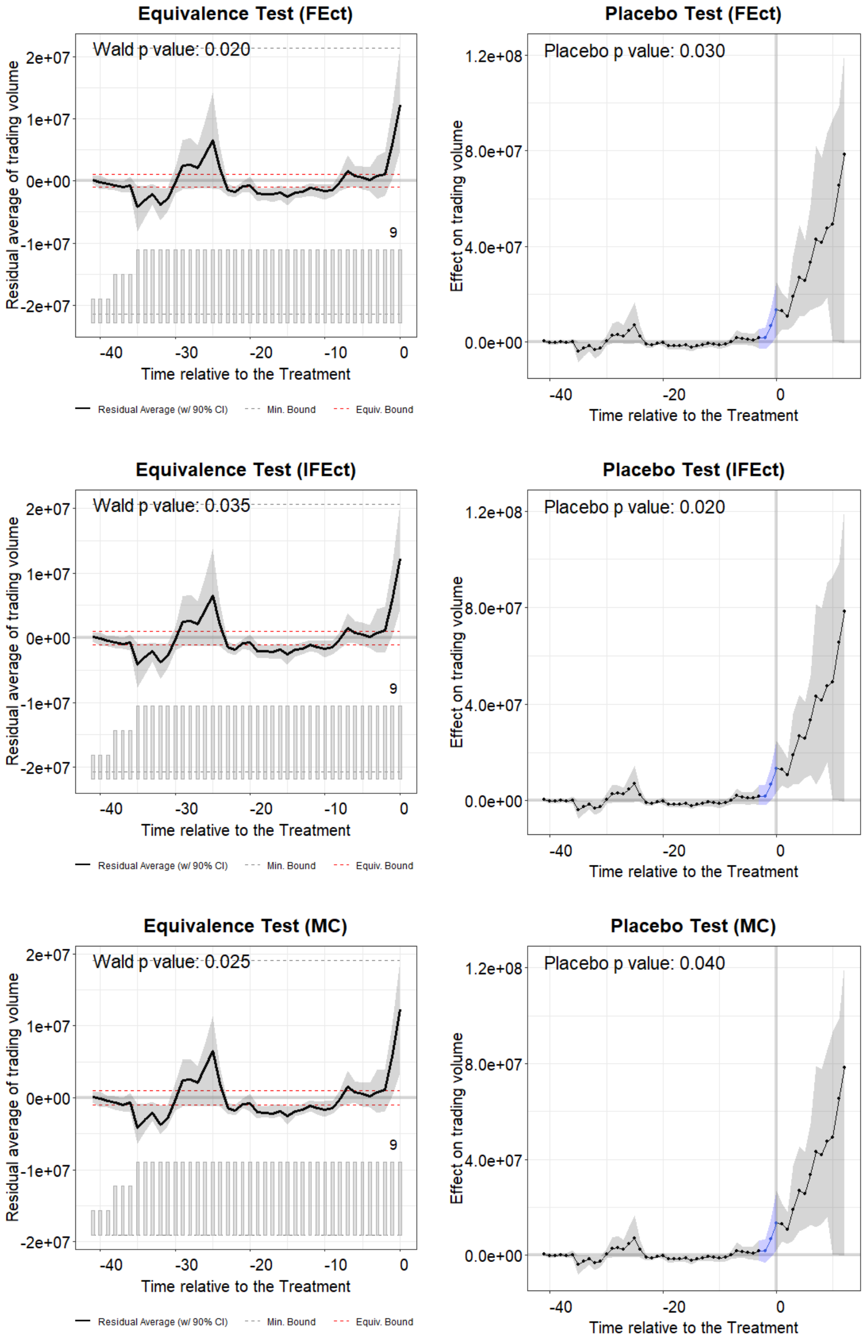


Figure 3.B2: Diagnostic Tests of Turnover

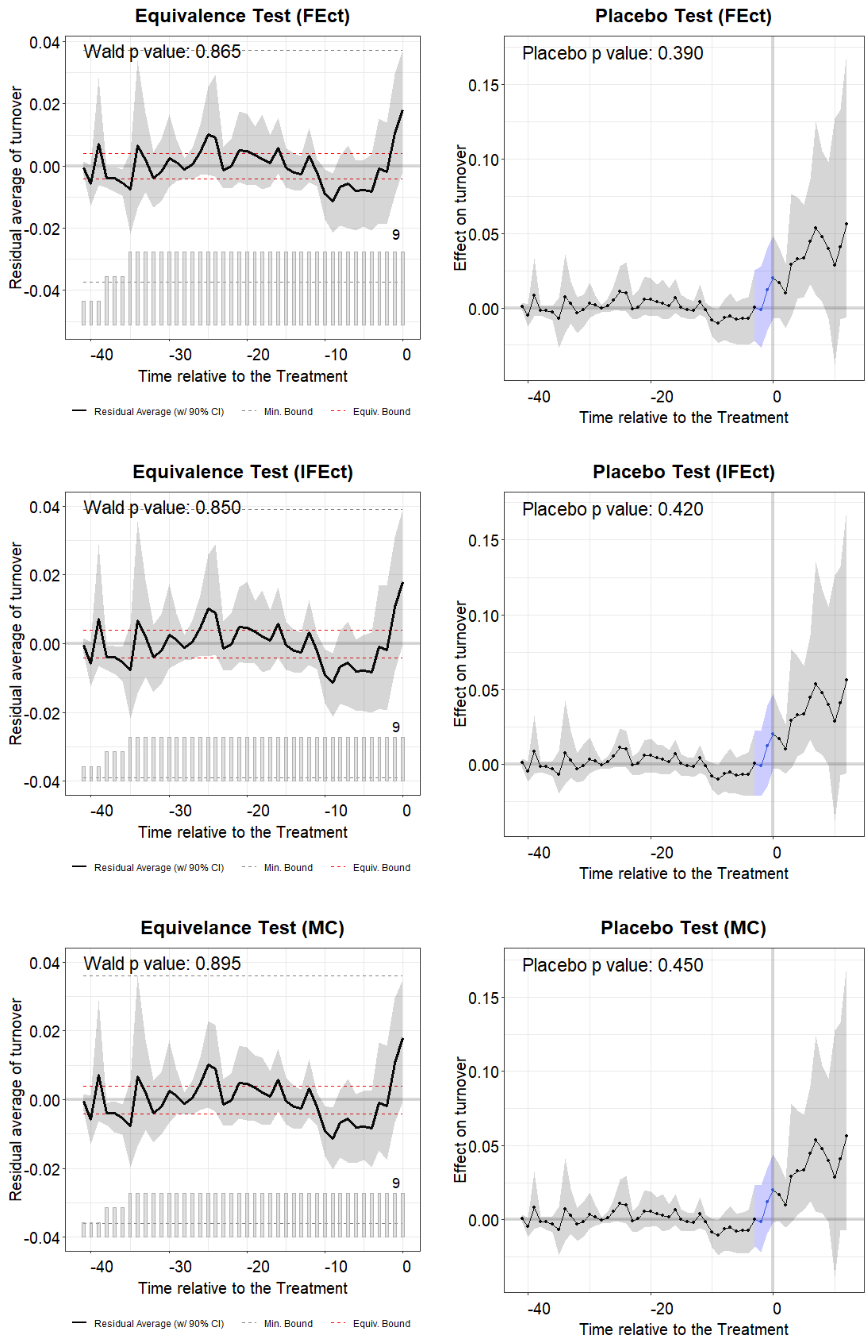


Figure 3.B3: Diagnostic Tests of Spread

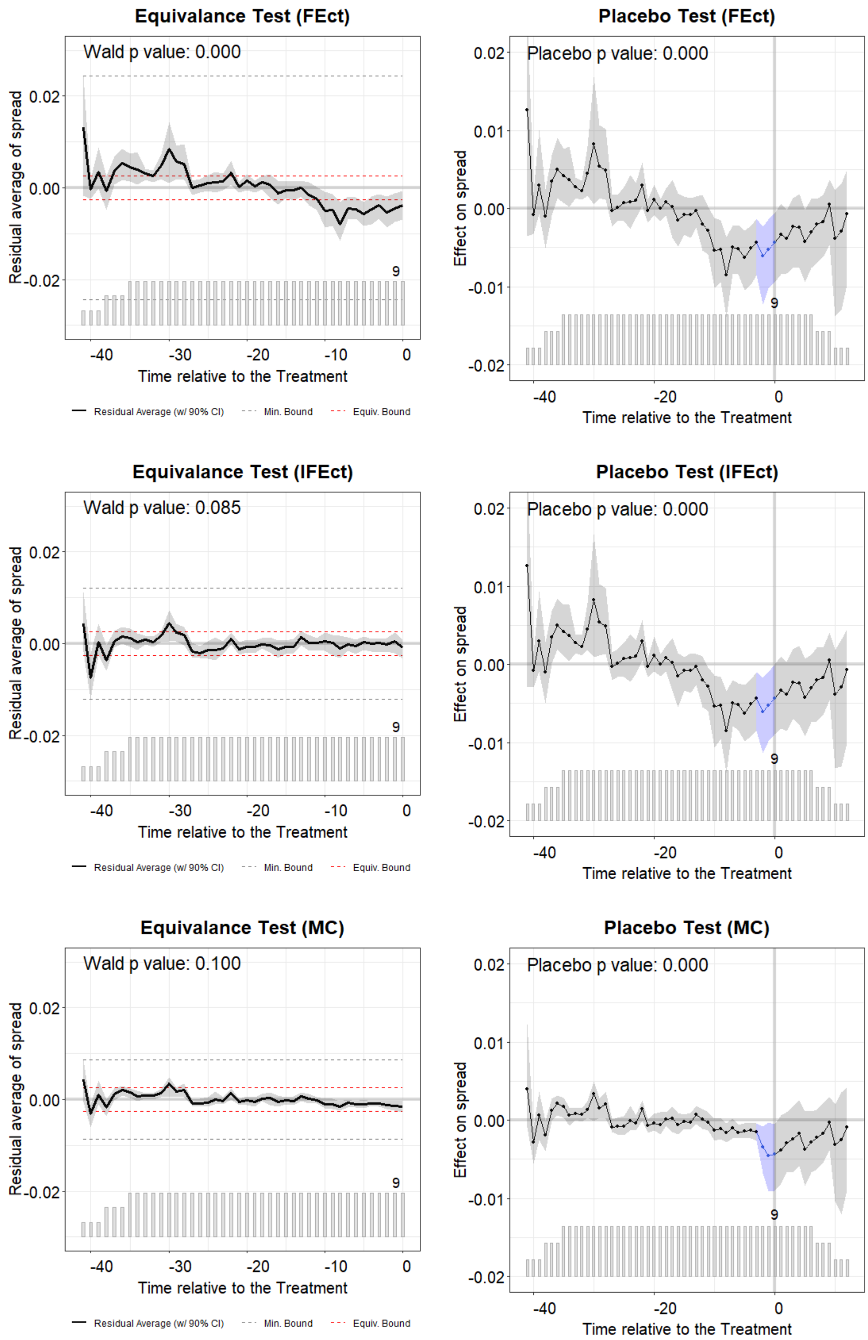


Figure 3.B4: Diagnostic Tests of Price Efficiency

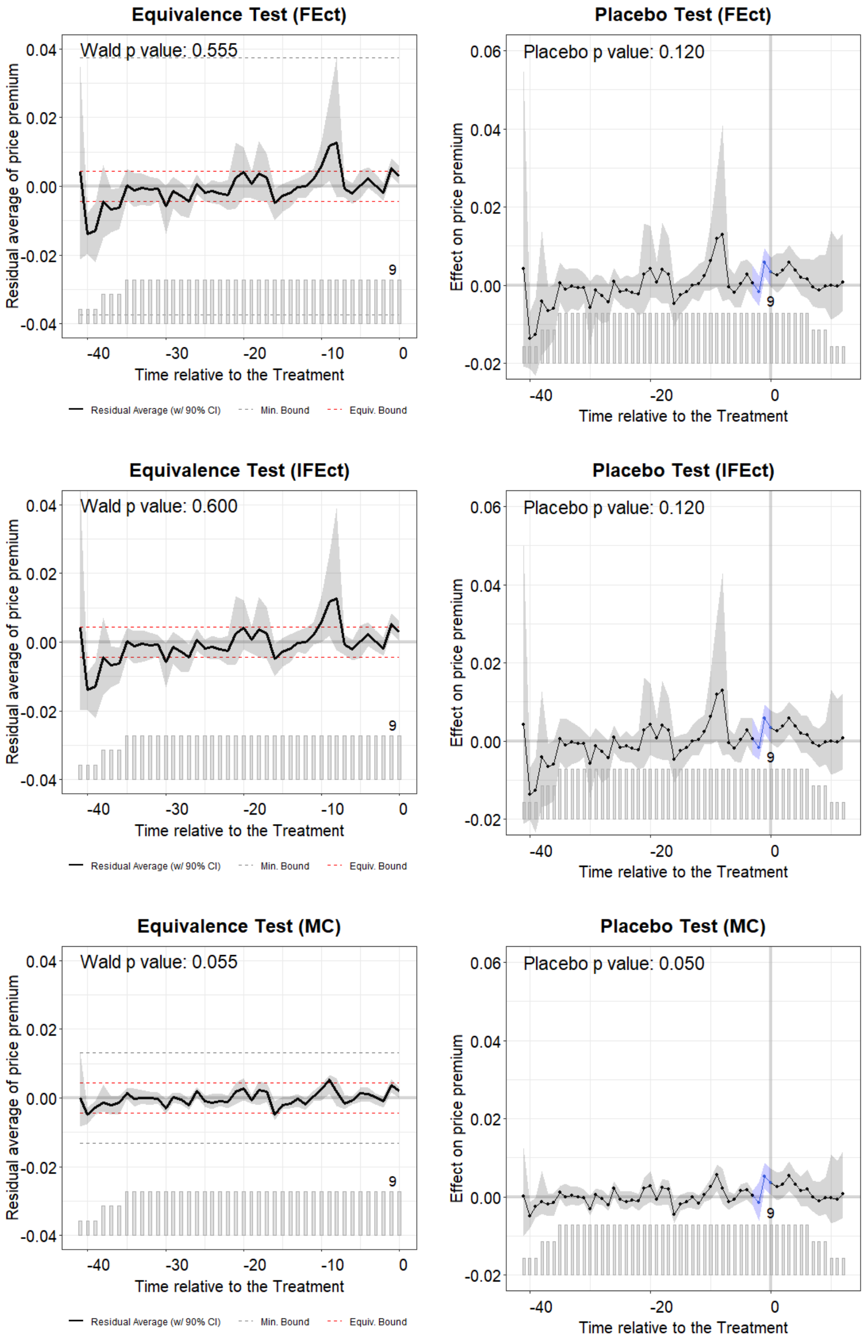


Figure 3.B5: Diagnostic Tests of Price Volatility

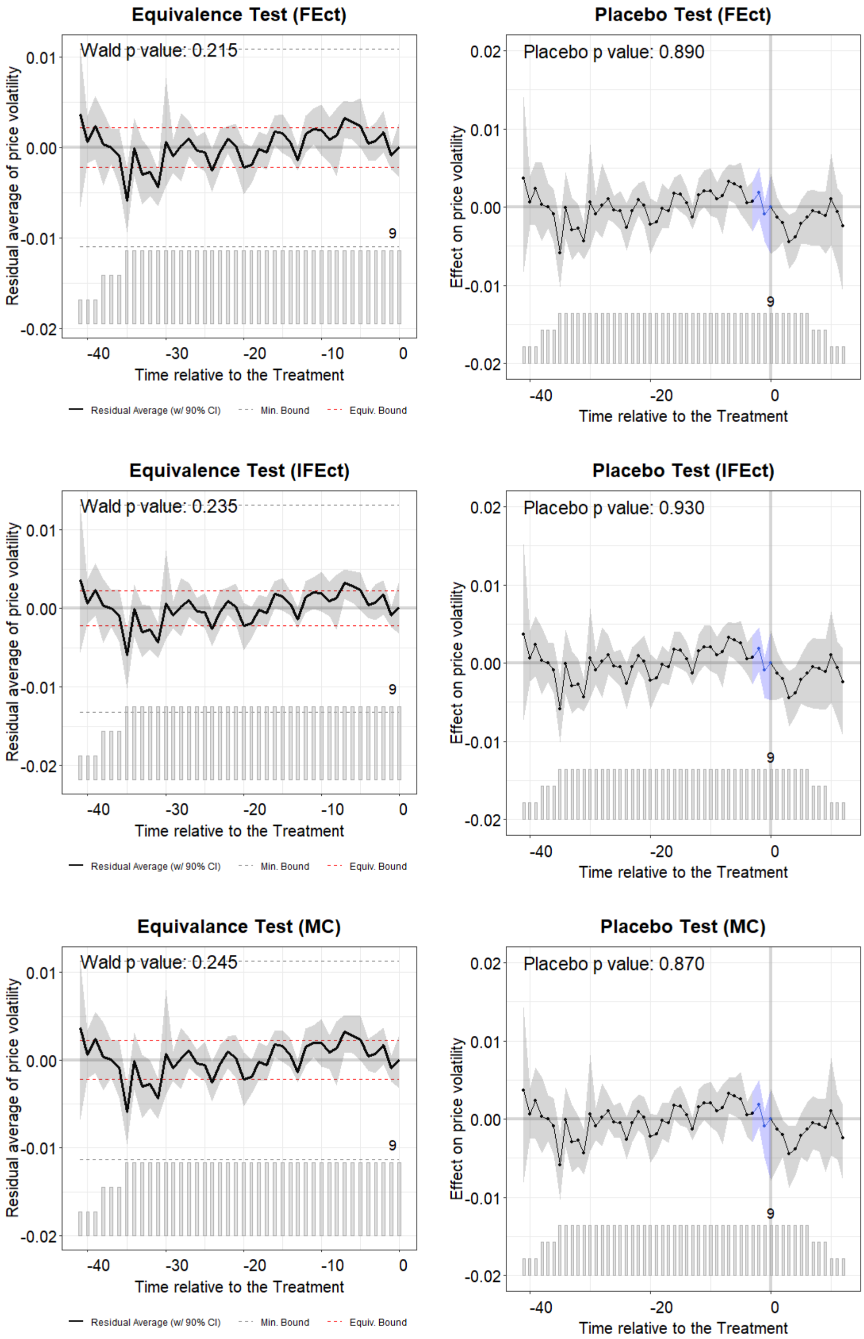
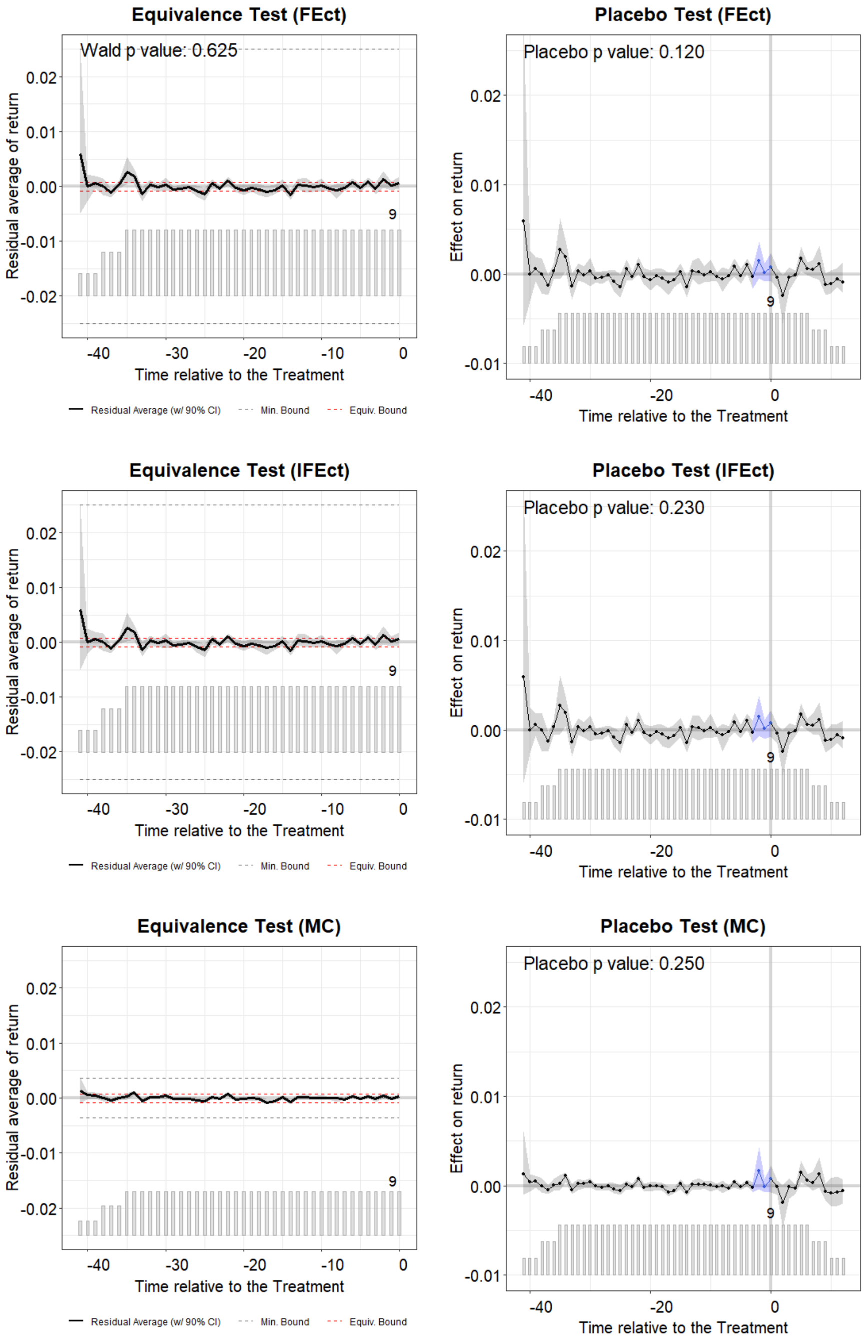


Figure 3.B6: Diagnostic Tests of Return



Chapter 4

The Causal Effect of Option Market Introductions: A Synthetic Control Approach

Abstract

This chapter investigates the effect of CSI 300 ETF options listing on targeted ETFs in the Chinese market from 2019 to 2020 by generalized synthetic control method (GSC) and the difference-in-differences (DiD) method. The short interest of treated ETFs declined immediately after the options listing but bounced back later, suggesting a transitory treatment effect. Both GSC and DiD methods indicate declines in returns and increases in trading volume after options were introduced, but the results concerning volatility are ambiguous. In general, the introduction of ETFs options relaxed short-sale constraints, and improved liquidity and efficiency in the underlying market. The ETF in the Shanghai market was subject to a more significant treatment effect than the ETF traded in the Shenzhen market.

4.1 Introduction

The effect of option market introductions on the underlying market quality has been debated for decades in developed markets, but the Chinese market has not introduced ETFs options until 2015. The classical Black-Scholes model (Black and Scholes, 1973) states that options are redundant in a complete and perfect market, and options listing should not influence underlying securities[1]. The introduction of options provides an alternative way for market traders to build synthetic short positions and overcome the difficulty of borrowing assets in a friction market. Besides, the advantage of transaction cost efficiency attracts market participants to option market. The deviations from the market assumptions can explain why some empirical findings support that option listing has substitution or complementary impact on the underlying assets (Blau and Wade, 2013; Kumar et al., 1995; Pilar and Rafael, 2002).

The initial motivation for the chapter is a realization that DiD methods requires a strict common trend assumption and restricts the general application of unbalanced panel data. Moreover, recent studies (Kahn-Lang and Lang, 2020) have warned that traditional pre-tests might fail to detect the violation of common trends and imply weak identification power of pre-testing. This chapter initially uses generalized synthetic control methods to evaluate the influence of option market introductions, which avoids the worry of common trend violation.

Figlewski (1981) states that a high level of short interest reflects high short selling constraints. Based on this explanation, my work is similar with Mayhew and Mihov (2005) and Danielson and Sorescu (2001), which provide empirical evidence of relaxing short-sale constraints after option market introductions. Differently, I find that the declined short interest ratio bounced back quickly, and the treatment effect of treated ETFs only existed for a short period. A possible explanation is high costs of short selling do not necessarily cause a shift from the lending market to the options market

[1]Like many modern finance theory which commonly based on portfolio replication argument, the Black-Scholes model requires an investor continuously adjust a portfolio which is made up by a stock and a risk-free bond to accurately replicate option returns of the stock. Theoretically, the option value should be equal to the value of the replication portfolio (a combination of stock and risk-free bond), then any option can be replicated by a continuously adjusted portfolio. In other words, options are redundant in a perfect market.

because short selling is necessary for investors holding put options to hedge risks (Blau and Wade, 2013).

I further analyse trading volume to understand the changes of short interest ratio. My findings are consistent with Pilar and Rafael (2002)'s study in the Spanish market, supporting the view that derivatives improve the trading volume of the underlying assets. Short interest ratio is defined as short selling volume divided by trading volume. When the trading volume increases constantly, the bounced short interest of treated ETFs is more likely driven by increased short selling volume, as a response of taking long positions in the underlying market. In this case, options play a complementary role between the ETF market and option market.

The short interest ratio is also referenced as a signal of the market return. On the one hand, Fosback (1976) believes that a high ratio of short interest is a bullish predictive signal because it reflects high demand and upward price pressure of the shorted securities in the near future. On the other hand, Asquith et al. (2005) and Desai et al. (2002) suggest that a high level of short interest is a bearish signal of returns and declined return rates under the theoretical model of Diamond and Verrecchia (1987). I find the declined return is consistent with the change of short interest ratio, supporting the overvaluation theory (Miller, 1977). The introduction of ETF options facilitates less restricted short selling activities by enabling pessimistic investors to establish short positions in the options market. Since bearish option strategies can be substitutes for short sales, it is unsurprising to see a significant reduction of short interest in the underlying ETF market.

Researchers and regulators have been concerned about whether option listings produce high return volatility and impede market quality. The Black-Scholes model (Black and Scholes, 1973) assumes market volatility is known, while the actual volatility is not a known constant parameter which changes over time in real world options trading and usually differs by sample selection. Difficulties in predicting accurate market volatility cause return and risk errors in options trading (Figlewski, 1989; Goyal and Saretto, 2009). A recent theoretical model proposed by Shi and Xiao (2020) states that volatility levels vary with the critical state and tightness between borrowing constraints and short selling constraints. Therefore, it is unclear whether derivatives such as options make markets more volatile from a theoretical standpoint.

The relevant empirical studies also hold different opinions about the impact of options on market stability. American and Japanese markets witnessed increased volatility after option listings (Liu, 2010; Robbani and Bhuyan, 2005). A possible explanation is that the increased liquidity in the underlying market (contributed by uninformed or irrational traders) had a destabilizing effect after option market introductions (Robbani and Bhuyan, 2005; Skinner, 1989). Other close studies (Arkorful et al., 2020; Chen and Chang, 2008; Sui et al., 2021) find significant declines in volatility after the first Chinese ETF options were introduced. My results on the volatility of ETF options are ambiguous. Indeed, this chapter finds significant declines in volatility by the DiD method, but the GSC method shows volatility of treated ETFs increased insignificantly after options were introduced. Similarly, Freund et al. (1994), Mayhew et al. (2000), and Bollen (1998) find short lived or no effect of option market introductions on stock volatility.

The rest of the chapter is organized as follows. Section 4.2 presents data collection and describes characteristics of the treated group and control group. Section 4.3 presents the methodology to test hypotheses. Section 4.4 compares treatment results of generalized synthetic control and difference-in-difference method. The final section is the conclusion.

4.2 Data

The sample includes two treated ETFs: the ETF 300 of Huatai-Pinebridge listed on the Shanghai Stock Exchange and the ETF 300 of Harvest Fund listed on the Shenzhen Stock Exchange, respectively. They have become the targets of the CSI 300 ETF options since 23rd December 2019. There are 42 ETFs in the control group, which have not been treated for any option. This chapter aims to analyze whether the options introductions have an impact on short selling activities. Thus, data from ETFs with margin trading and short selling qualification in the Chinese market is considered in this study. This sample collects data from 1st January 2019 to 31st March 2020, downloaded from RESSET, and averages daily data to a weekly frequency.

The ideal control group should be made of ETFs with the same tracking index as treated ETFs, but this selection standard can not generate ideal counterfactual outcomes as expected. The main reason is that ETFs update margin trading and short selling list quarterly in my sample periods, and not all of them remain in the list consistently. Only four ETFs have the same tracking index (CSI 300 Index) as treated ETFs; especially, they have many missing values about the essential variable—short selling volume. Thus, I expanded the control group, including ETFs with similar market indexes such as CSI 500 and SSE 50 and other indexes with relevant close features to the treated ETFs. The two treated ETFs and 42 ETFs in control group are listed in Appendix Table 4.5.

Characteristics of Treated and Control ETFs

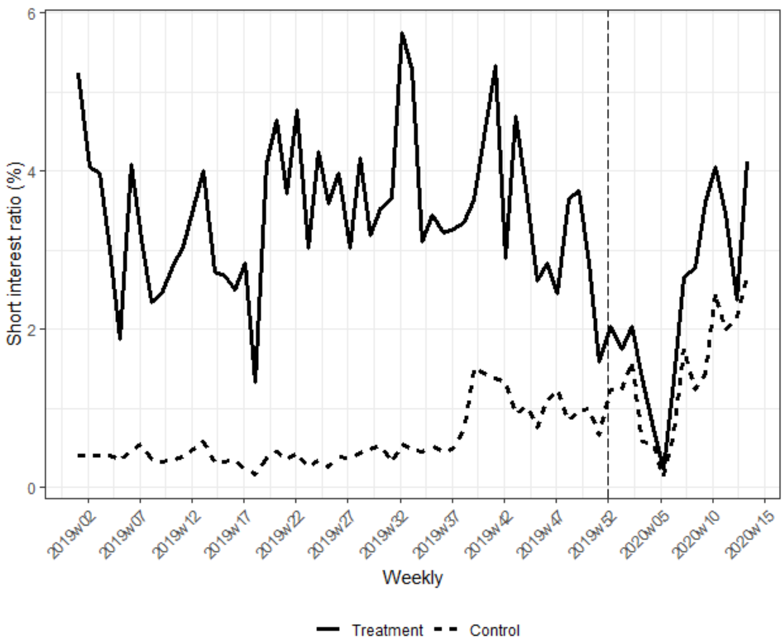


Figure 4.1: Short Interest Ratio of Treated and Control ETFs

Figure 4.1 demonstrates the short interest ratio of treated ETFs and control ETFs. The short interest ratio is the percentage of short selling shares divided by trading volume. Before the intervention, the average short interest ratio of control ETFs remained low, but the treated ETFs fluctuated highly. The average short interest ratio of control ETFs is less than 1 % in most pre-treatment periods, while treated

ETFs have more than 3 % short interest ratio in most trading weeks. At the start of 2019, treated ETFs have more than 5 % average short interest ratio, whereas the number of control ETFs is around 0.5 %. There is a noticeable short interest decline of all ETFs in the first month in post-treatment periods. Both groups' short interest ratio reaches the same lowest point, approximately 0.5 %. The short interest ratio of treated ETFs bounces back to the pre-treatment level immediately. Surprisingly, the control ETFs show an increasing trend of short interest in the second month after the ETF 300 options introductions, which is almost doubled at the end of observed sample periods. Intuitively, Figure 4.1 shows that a common trend does not exist between treated ETFs and control ETFs in this sample.

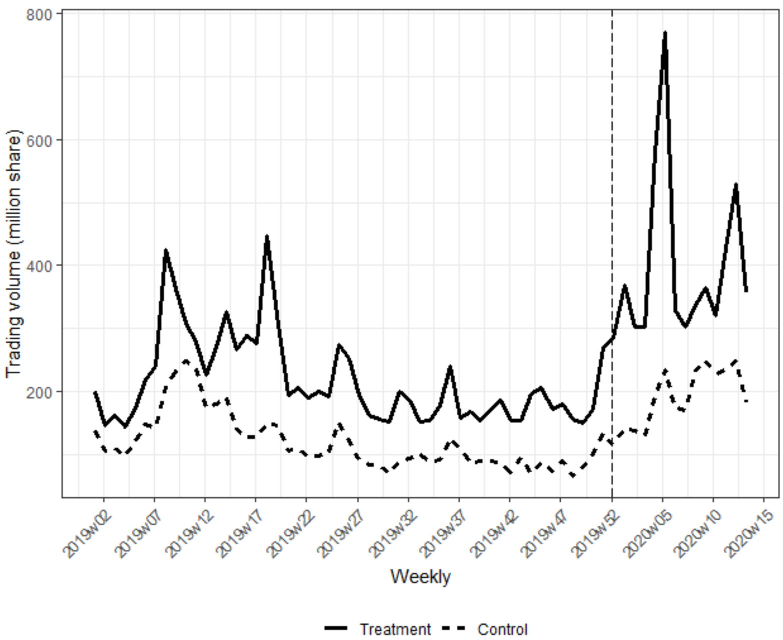


Figure 4.2: Trading Volume of Treated and Control ETFs

Figure 4.2 gives information about trading volume between January 2019 to March 2020. ETF 300 option seems to tend to select targeted ETFs with relatively active trading activities and large sizes. Both treated and control trading volumes rise over the period, but figures for treated ETFs are significantly higher and peak around one month after the ETF 300 options introductions. In January 2019, less than 200 million shares of both treated and control ETFs are traded on average. The number trading volume in the treated group stand at just under 800 million shares around February 2020. After the second month of ETF 300 options introductions, the average trading volume of treated ETFs remains more than 300 million shares, but the rest control ETFs increase slightly. The average trading volume of control ETFs peak at around 250 million shares during post-treatment periods, showing the same pre-treatment peak record in March 2019. In sum, the trading volume shares are almost doubled in both treated and control ETFs at the end of the first quarter in 2020, respectively, but treated ETFs have a much higher peak trading volume after the intervention.

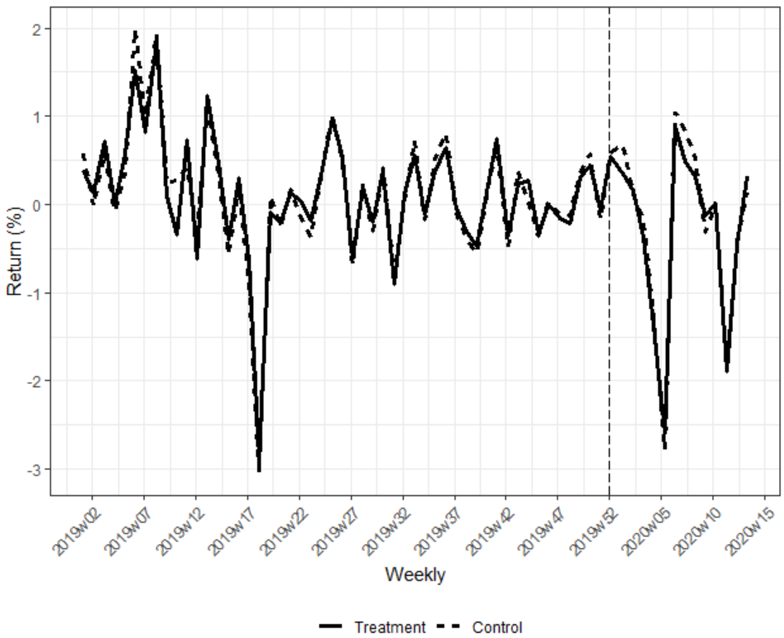


Figure 4.3: Return of Treated and Control ETFs

Figure 4.3 compares the return rates of treated and control ETFs over five quarters. Return rate has small differences during the whole sample period. The treated ETFs are expected to see a significant decline after options introductions since the options market may reduce short selling, and prices may fall accordingly. However, the average return differences between treated and control were tiny. Return rate in both treated and control groups falls suddenly in February 2020, close to the lowest return in May 2019 around −3%. Another possible reason is the coronavirus pandemic; return rates after intervention fluctuated more than returns before the intervention.

It is clear from Figure 4.4 that the overall volatility in the post-treatment time is much higher than the pre-treatment record in both treated and control ETFs. Generally, the average volatility of treated ETFs is higher than the counterparts

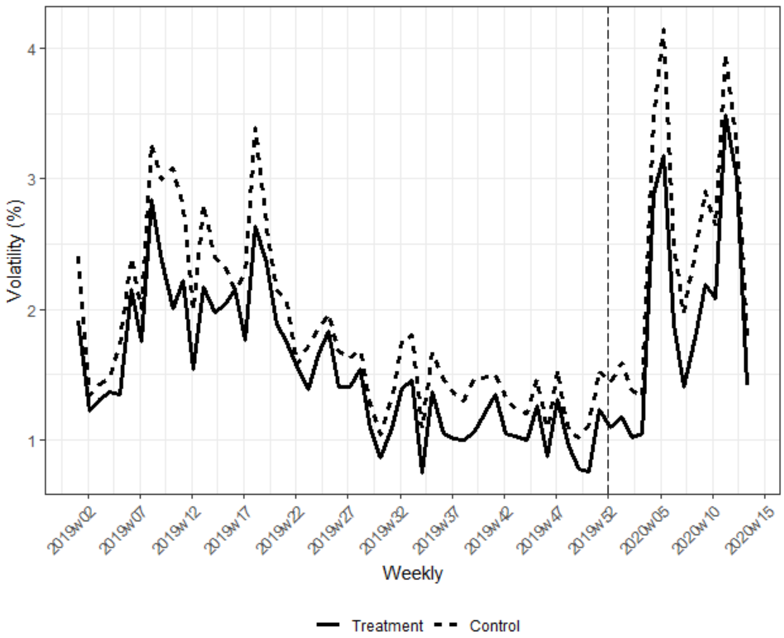


Figure 4.4: Volatility of Treated and Control ETFs

during the sample period. All ETFs' volatility is relatively high in the first half-year in 2019, which ranges from 1 % to 3.5 %. Later, the volatility remains low until February 2020 and reaches over 3 % for both treated and control ETFs. It is unclear whether ETF300 options introductions cause higher volatility or other market reasons from this graph.

4.3 Methodology

4.3.1 Overview of Synthetic Control Methods

Doudchenko and Imbens (2016) and Chernozhukov et al. (2021) category causal effect estimation approaches, including DiD, matching methods[2], synthetic control methods[3], and regression models[4]. The DiD method probably is the most popular one in policy evaluation studies. One of the attractive properties of DiD method is that it can remove time-invariant differences between treated units and control

[2]e.g., Hirano et al. (2003)
[3]e.g., Abadie et al. (2010, 2015); Abadie and Gardeazabal (2003)
[4]e.g., De Chaisemartin and d'Haultfoeuille (2020); Gobillon and Magnac (2016); Hsiao et al. (2012); Imai and Kim (2021)

units, but it assumes treatment effects of these confounders are constant over time. Synthetic control method only assumes that the averaged treated group and the weighted average synthetic estimation based on control group satisfy a parallel trends over sample period. Therefore, a growing number of researches (Abraham and Sun, 2018; Arkhangelsky et al., 2019) try to combine advantages of DiD and synthetic control.

The synthetic control method is initially proposed by Abadie and Gardeazabal (2003) to exam the effect of terrorism on GDP in the Basque country using other Spanish regions as control group. Abadie et al. (2010) and Abadie et al. (2015) use the synthetic control method for further comparative case studies, which apply one treated unit, a small number of control units and low frequent data. These studies show that synthetic control method is an ideal alternative method when there is no single counterpart with similar characteristics for accurate treatment effect estimation. Generally, pre-treatment periods should longer than post-treatment periods in order to generate better counterfactual estimations. Therefore, Abadie et al. (2015) against the original synthetic control method when the pre-treatment cannot fit well and the number of pre-treatment observations is small.

In the later series of extended synthetic control methods attempt to revise model setting of the original synthetic control method for a more general application. For instance, Amjad et al. (2018); Arkhangelsky et al. (2019); Chernozhukov et al. (2021); Doudchenko and Imbens (2016) revise the original synthetic method for large sample estimation by adding penalization term to restrict the sum of weights. Ferman and Pinto (2019), Amjad et al. (2018), and Ben-Michael et al. (2021) allow negative weights and aim to overcome the challenges of imperfect pre-treatment synthetic. Athey and Imbens (2016) propose an "honest" approach to estimate heterogeneity causal effect without sparsity assumption, but their data-driven method specifies a strong assumption of complete randomization.

4.3.2 Generalized Synthetic Control Method

I follow the notion of Xu (2017) for the generalized synthetic control model settings. In this sample, there are two treated units—ETF 159919 in Shenzhen market and

ETF 510300 in Shanghai market exposed to the option introduction program at the same intervention time T_0, where the number of treated units is denoted to N_{tr} and the treated group is denoted to $\mathcal{T}$. There are 42 controlled ETFs that remain unexposed to option introduction program during all observed periods. The number of controlled units is denoted to N_{co} and the control group is denoted to $\mathcal{C}$.

Assumption 1: functional form

$$y_{it} = \delta_{it} D_{it} + x_{it}'\beta + \omega_i' f_t + \varepsilon_{it}, \tag{4.1}$$

where D_{it} is the treatment indicator and has value 1 only if unit i in treated group is exposed to treatment ($i \in \mathcal{T}$ and $t > T_0$). x_{it} is a $p \times 1$ vector of observed covariates, and $\beta = [\beta_1, ..., \beta_p]'$ is a p dimensional observed covariates vector. The factor component part $\omega_i' f_t = [\omega_{i1} f_{1t} + \omega_{i2} f_{2t} + ... + \omega_{ir} f_{rt}]$ has a linear additive form, where $\omega_i = [\omega_{i1}, ..., \omega_{ir}]'$ is an $(r \times 1)$ unknown factor loadings and $f_t = [f_{1t}, ..., f_{rt}]'$ is an $(r \times 1)$ unobserved common factors vector. Specifically, if we let $f_{1t} = 1, f_{2t} = \xi_t, \omega_{i1} = \alpha_i$ and $\omega_{i2} = 1$, the functional form will be a conventional unit and time fixed effects model $y_{it} = \delta_{it} D_{it} + x_{it}'\beta + \alpha_i + \xi_t$. ε_{it} are idiosyncratic error terms with zero mean. There are two possible outcomes $y_{it}(0) = x_{it}'\beta + \omega_i' f_t + \varepsilon_{it}$ and $y_{it}(1) = \delta_{it} + x_{it}'\beta + \omega_i' f_t + \varepsilon_{it}$, which correspond $D_{it} = 0$ and $D_{it} = 1$, respectively. $\delta_{it} = y_t(1) - y_{it}(0)$ ($\forall i \in \mathcal{T}$ and $t > T_0$) measures the treatment effect on unit i at time t.

Assumption 2: strict exogeneity

$$\varepsilon_{it} \perp\!\!\!\perp \{D_{js}, X_{js}, \Omega_j, f_s\} \quad \forall i, j, t, s$$

Assumption 3: regularity conditions

For control group N_{co}, we can write to a compactly matrix notation

$$\boldsymbol{Y(0)} = \boldsymbol{X}\beta + \boldsymbol{F\Omega}' + \boldsymbol{\varepsilon}, \tag{4.2}$$

$$\boldsymbol{F'F/T} = \boldsymbol{I_r}, \quad \boldsymbol{\Omega'\Omega} = diagonal.$$

$\boldsymbol{Y}(0)$ is the outcomes of control group with $(T \times N)$ dimension; $\boldsymbol{X}$ is a $(T \times N \times p)$ matrix and the product $\boldsymbol{X}\beta$ is $T \times N$; the factor component part $\boldsymbol{F\Omega}$ and is $T \times N$ dimensional matrices, in which $\boldsymbol{F} = [F_1, F_2, ..., F_T]'$ is a $T \times r$ matrix, and $\boldsymbol{\Omega} = [\Omega_1, \Omega_2, ..., \Omega_N]'$ is a $N \times r$ matrix; $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, ..., \varepsilon_N]$ is a $(T \times N)$ matrix of idiosyncratic errors. Bai (2009) explains that in the view of $\boldsymbol{F\Omega' = FAA^{-1}\Omega'}$ for an arbitrage $r \times r$ invertible $\boldsymbol{A}$ has r^2 free elements and needs r^2 restrictions for model identification. The normalization constraint on factors $\boldsymbol{F'F/T = I_r}$ yields $r(r+1)/2$ restrictions and the orthogonal constraint on factor loadings $\boldsymbol{\Omega'\Omega} = \textit{diagonal}$ generates $r(r-1)/2$ restrictions. Other factor analysis studies (Bai and Ng, 2002; Stock and Watson, 2002) also add similar factors and factor loadings assumptions.

After imposing the normalization and diagonal restrictions, we will have the factor loadings matrix in the following form:

$$\boldsymbol{\Omega} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \omega_{21} & 1 & \cdots & 0 \\ & & \vdots & \\ \omega_{r1} & \omega_{r2} & \cdots & 1 \\ & & \vdots & \\ \omega_{N1} & \omega_{N2} & \cdots & \omega_{Nr} \end{bmatrix}.$$

In the absence of β, we have $y_{1t} = f_{1t} + \varepsilon_{1t}$, which is the first factor plus an idiosyncratic error. Iteratively, we have $y_{2t} = \omega_{21} f_{1t} + f_{2t} + \varepsilon_{2t}$ or $y_{2t} = \omega_{21} y_{1t} + f_{2t} + \varepsilon^*_{2t}$, and so on.

Estimation of Average Treatment Effect

As the treated ETF i at time t has estimated treated effect δ_{it}, which is the difference between its actual outcome and estimated counterfactual outcome. The estimated average treatment effect is the arithmetic mean value of treated ETFs:

$$\frac{y_{it} - \hat{y}_{it}(0)}{N_{tr}}, \qquad t > T_o, \tag{4.3}$$

where N_{tr} is the number of treated ETFs, T_o is the intervention time. Bai (2009) propose the following method to estimate $\hat{y}_{it}(0)$, which can compute β by given $\boldsymbol{F}$ or compute $\boldsymbol{F}$ by given β.

We aim to obtain the least squares object function:

$$(\hat{\beta}, \hat{\boldsymbol{F}}, \hat{\boldsymbol{\Omega}}) = arg\,min \sum_{i=1}^{N_{co}} (\boldsymbol{Y}_i - \boldsymbol{X}_i\tilde{\beta} - \tilde{\boldsymbol{F}}\tilde{\boldsymbol{\Omega}}_i)'(\boldsymbol{Y}_i - \boldsymbol{X}_i\tilde{\beta} - \tilde{\boldsymbol{F}}\tilde{\boldsymbol{\Omega}}_i). \tag{4.4}$$

The constraints $\tilde{\boldsymbol{F}}'\tilde{\boldsymbol{F}}/T = \boldsymbol{I}_r$ and $\tilde{\boldsymbol{\Omega}}'\tilde{\boldsymbol{\Omega}} = diagonal$ are also applied at equation 4.3.2. Define the projection matrix:

$$\boldsymbol{N} = \boldsymbol{I}_r - \boldsymbol{F}(\boldsymbol{F}'\boldsymbol{F})^{-1}\boldsymbol{F}', \tag{4.5}$$

which can rewrite as

$$\boldsymbol{N} = \boldsymbol{I}_r - \boldsymbol{F}(T\boldsymbol{I}_r)^{-1}\boldsymbol{F} = \boldsymbol{I}_r - \boldsymbol{F}(\boldsymbol{I}_r/T)\boldsymbol{F}' = \boldsymbol{I}_r - (\boldsymbol{F}\boldsymbol{I}_r\boldsymbol{F}')/T = \boldsymbol{I}_r - \boldsymbol{F}\boldsymbol{F}'/T. \tag{4.6}$$

Given $\boldsymbol{F}$, we can get the estimated $\hat{\beta}$ by

$$\hat{\beta}(\boldsymbol{F}) = \left(\sum_{i=1}^{N_{co}} \boldsymbol{X}_i'\boldsymbol{N}\boldsymbol{X}_i\right)^{-1} \sum_{i=1}^{N_{co}} \boldsymbol{X}_i'\boldsymbol{N}\boldsymbol{Y}_i. \tag{4.7}$$

Given β, we can estimate $\boldsymbol{F}$ from a pure factor model $\boldsymbol{Y}_i - \boldsymbol{X}_i\beta = \boldsymbol{F}\boldsymbol{\Omega}_i + \boldsymbol{\varepsilon}_i$.

Let $\boldsymbol{W} = \boldsymbol{Y}_i - \boldsymbol{X}_i\beta = [W_1, W_2, ..., W_N]$, which is a $T \times N$ matrix. We write the pure factor model as

$$\boldsymbol{W} = \boldsymbol{F}\boldsymbol{\Omega} + \boldsymbol{\varepsilon}, \tag{4.8}$$

and its least squares function is

$$tr[(\boldsymbol{W} - \boldsymbol{F}\boldsymbol{\Omega}')(\boldsymbol{W} - \boldsymbol{F}\boldsymbol{\Omega}')'] \tag{4.9}$$

Optimizing the objection function turns to

$$tr(\boldsymbol{W}'\boldsymbol{N}\boldsymbol{W}) = tr(\boldsymbol{W}'(\boldsymbol{I}_r - \boldsymbol{F}\boldsymbol{F}'/T)\boldsymbol{W}) = tr(\boldsymbol{W}'\boldsymbol{W}) - tr(\boldsymbol{F}'\boldsymbol{W}\boldsymbol{W}'\boldsymbol{F}/T), \tag{4.10}$$

Therefore, we focus on maximizing $tr(\boldsymbol{F}'\boldsymbol{W}\boldsymbol{W}'\boldsymbol{F}/T)$, in which

$$\boldsymbol{W}\boldsymbol{W}' = \sum_{i=1}^{N_{co}} \boldsymbol{W}_i\boldsymbol{W}_i' = (\boldsymbol{Y}_i - \boldsymbol{X}_i\beta)(\boldsymbol{Y}_i - \boldsymbol{X}_i\beta)' \tag{4.11}$$

The factor component $\boldsymbol{F\Omega}'$ can be expressed as

$$\boldsymbol{F\Omega}' = \frac{\boldsymbol{F}'}{\sqrt{T}}\boldsymbol{W}\frac{\boldsymbol{F}}{\sqrt{T}}, \tag{4.12}$$

where $\frac{\boldsymbol{F}'}{\sqrt{T}} = \frac{\boldsymbol{F}^{-1}}{\sqrt{T}}$.

Multiply $\boldsymbol{F}^{-1}$ in both sides

$$\boldsymbol{\Omega}' = \frac{\boldsymbol{F}^{-1}\boldsymbol{F}'\boldsymbol{W}\boldsymbol{F}}{T} = \boldsymbol{F}'\boldsymbol{W}/T. \tag{4.13}$$

The factor loadings matrix can be written as

$$\boldsymbol{\Omega} = \boldsymbol{W}'\boldsymbol{F}/T. \tag{4.14}$$

The estimated $(\hat{\beta}, \hat{\boldsymbol{F}})$ is obtained literately by the solution of the set of equation 4.7 and

$$[\frac{1}{N_{co}T}\sum_{i=1}^{N_{co}}(\boldsymbol{Y}_i - \boldsymbol{X}_i\hat{\beta})(\boldsymbol{Y}_i - \boldsymbol{X}_i\hat{\beta})']\hat{\boldsymbol{F}} = \hat{\boldsymbol{F}}\boldsymbol{V}, \tag{4.15}$$

where $\boldsymbol{V}$ is an $N \times T$ diagnoal matrix with r largest eigenvalues in a decreasing order.

The estimated factor loadings matrix can also be written as

$$\hat{\boldsymbol{\Omega}} = \hat{\boldsymbol{F}}(\boldsymbol{Y}_i - \boldsymbol{X}_i\hat{\beta})/T. \tag{4.16}$$

In sum, given $\boldsymbol{F}$, we can get $\hat{\beta}$ by equation 4.7; given β, we can get $\hat{\boldsymbol{F}}$ and $\hat{\boldsymbol{\Omega}}$ by equation 4.15 and equation 4.16, respectively. The estimated set of $(\hat{\beta}, \hat{\boldsymbol{F}}, \hat{\boldsymbol{\Omega}})$ minimises the objective function 4.4 together.

Matrix Completion Estimation

The essential part of synthetic control method is how to estimate counterfactual outcomes of treated units based on observed information. In other words, what would be the performance of these two treated ETFs after time T_0 if ETF 300 option is not introduced. We can start from the control group for forecasting missing values and rewrite the function form more compactly. Let $\boldsymbol{Y} = [y_{it}]_{i=1,2,...,N,t=1,2,...,T}$ be an incomplete $N \times T$ matrix, where y_{it} denotes t week's short interest ratio (or trading volume, return rate, volatility) of ETF i in Chinese ETF market. Consist with chapter 3, I use D_{it} as treatment indicators and $\boldsymbol{D}_{N\times T} = [D_{it}]_{i=1,2,\ldots,N,t=1,2,\ldots,T}$. In order to label the positions of missing entries and observed entries, I denote E as the set of pairs of indices (i,t), $i \in [N]$, $t \in T$ to label the missing entries ($D_{it} = 1$) in matrix $\boldsymbol{Y}$, and O is the set of pairs of indices, (i,t), $i \in [N]$, $t \in T$ corresponding to the observed entries ($D_{it} = 0$) in matrix $\boldsymbol{Y}$. If $(i,t) \in E$, then $D_{it} = 1$; if $(i,t) \in O$, then $D_{it} = 0$.

Follow the matrix completion equation (3.3) that omits covariates in the previous chapter:

$$y_{it} = \delta_{it} D_{it} + \boldsymbol{M} + \boldsymbol{\varepsilon}.$$

The matrix completion approach aims to impute missing entries in the $N \times T$ matrix $\boldsymbol{M}$. The non-treated potential outcomes:

$$y_{it}(0) = \boldsymbol{M} + \boldsymbol{\varepsilon}, \tag{4.17}$$

where $\boldsymbol{M} = [M_{it}]_{i=1,2,\ldots,N,t=1,2,\ldots,T}$, and $\boldsymbol{\varepsilon}$ is an $(N \times T\ )$ matrix of errors. The matrix completion method seeks to solve the minimization problem which is discussed in chapter 3 equation (3.13):

$$\hat{\boldsymbol{M}} = \arg\min[\sum_{i=1}^{N_{co}} \frac{(y_{it} - M_{it})^2}{N_{co}} + \theta \|\boldsymbol{M}\|],$$

where θ is the tuning parameter or the penalty factor.

I summarize Athey and Imbens (2018)'s method to complete the $N \times T$ outcomes matrix $\boldsymbol{Y}$ in the following, which is called the matrix-completion with nuclear norm minimization estimator or penalty factor:

Define $\boldsymbol{P}_O(\cdot)$ and $\boldsymbol{P}_O^{\perp}(\cdot)$ for any matrix $\boldsymbol{R}$.

$$\boldsymbol{P}_O(\boldsymbol{R})_{it} = \begin{cases} \boldsymbol{R}_{it} & \text{if } (i,t) \in O, \\ 0 & \text{if } (i,t) \notin O, \end{cases}$$

and

$$\boldsymbol{P}_O^{\perp}(\boldsymbol{R})_{it} = \begin{cases} \boldsymbol{R}_{it} & \text{if } (i,t) \notin O, \\ 0 & \text{if } (i,t) \in O, \end{cases}$$

where $\boldsymbol{P_O}(\boldsymbol{R}) + \boldsymbol{P}_O^{\perp}(\boldsymbol{R}) \equiv \boldsymbol{R}$. For example, if $\boldsymbol{R} = \begin{bmatrix} 2 & ? \\ ? & 4 \end{bmatrix} \in \mathbb{R}^{2\times 2}$ is a partly observed matrix, and $O = \{(1,1),(2,2)\}$ labels the observed elements, then we have $\boldsymbol{P_O}(\boldsymbol{R}) = \begin{bmatrix} 2 & 0 \\ 0 & 4 \end{bmatrix} \in \mathbb{R}^{2\times 2}$.

Given the Singular Value Decomposition (SVD) for matrix $\boldsymbol{R}$, $\boldsymbol{R} = \boldsymbol{U\Sigma V}^{\mathrm{T}}$, and $\boldsymbol{\Sigma}$ is diagonal with ordered $\sigma_i(\boldsymbol{R})$. The matrix shrink operator is defined as:

$$Shrink_{\theta}(\boldsymbol{R}) = \boldsymbol{U\Sigma}_{\theta}\boldsymbol{V}^{\mathrm{T}}, \tag{4.18}$$

where $(\boldsymbol{\Sigma}_{\theta})_{ii} = \max\{\boldsymbol{\Sigma_{ii}} - \boldsymbol{\theta}, 0\}$, θ is the penalty factor which is chosen through cross-validation . $\boldsymbol{\Sigma}$ and $\boldsymbol{\Sigma}_{\theta}$ can be expressed as [5]

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & 0 & \cdots & 0 \\ 0 & \sigma_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & |\sigma_i| \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}_{N\times T}, \quad \boldsymbol{\Sigma_{\theta}} = \begin{bmatrix} |\sigma_1 - \theta|_+ & 0 & 0 & \cdots & 0 \\ 0 & |\sigma_2 - \theta|_+ & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & |\sigma_i - \theta|_+ \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}_{N\times T}.$$

The interactive process is:

$$\boldsymbol{M}_{k+1}(\theta, O) = \mathrm{Shrink}_{\frac{\theta|O|}{2}}\left\{\boldsymbol{P}_O(\boldsymbol{Y}) + \boldsymbol{P}_O^{\perp}(\boldsymbol{M}_k(\theta, O))\right\}, \tag{4.19}$$

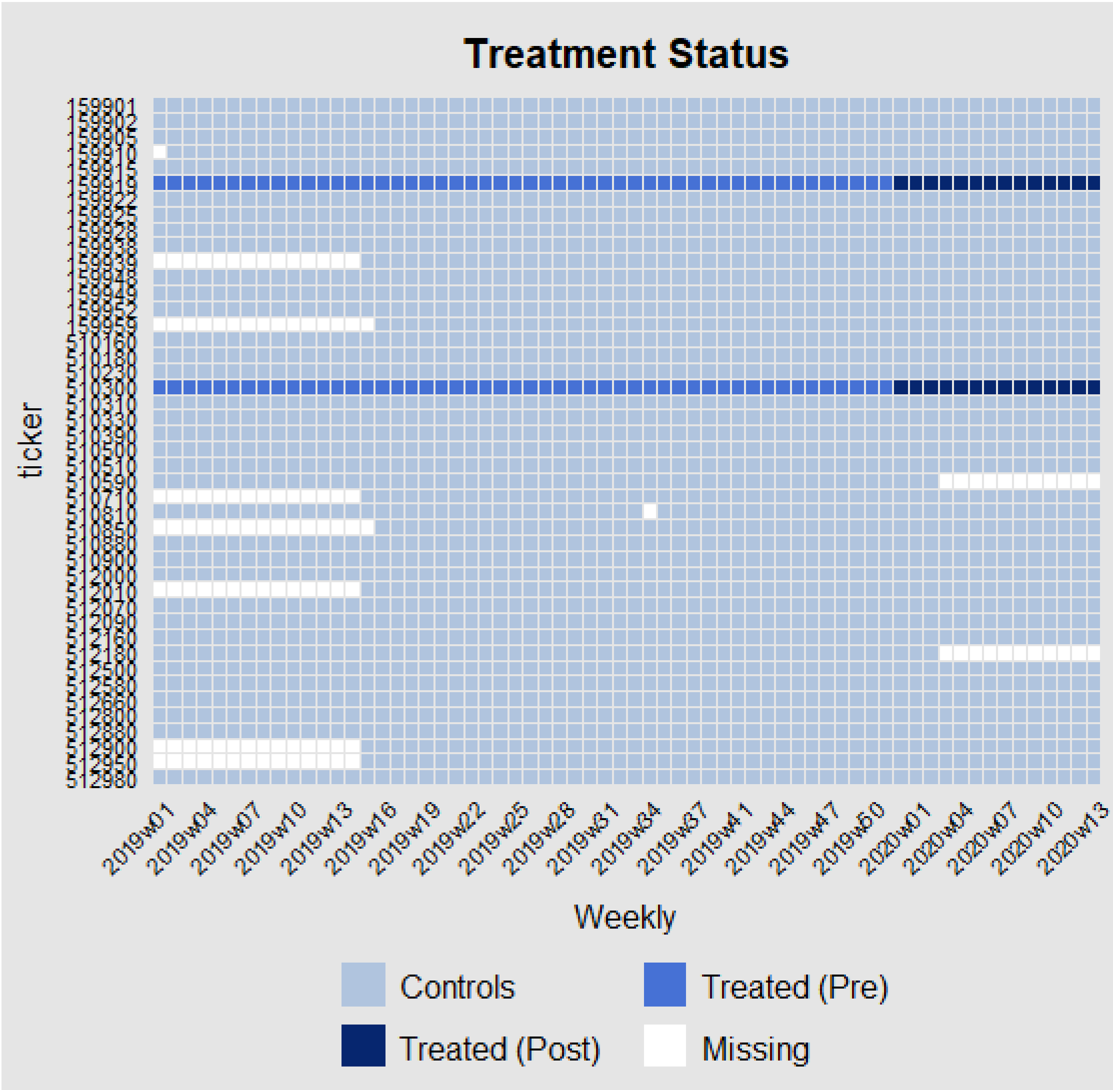
where $k = 1, 2, ...,$ and we start with an initial value $\boldsymbol{M}_1(\theta, O) = \boldsymbol{P}_O(\boldsymbol{Y})$. Equation (4.19) repeats until the sequence $\left\{\boldsymbol{M}_k(\theta, O)\right\}_{k>1}$ converge.

The number of units N and time periods T influences treatment estimation results in conventional synthetic control method, while it is less sensitive in matrix completion

[5] $|\sigma_i - \theta|_+ = \max\{(\sigma_i - \theta), 0\}$

estimation [6]. Figure 4.5 shows the data structure of this chapter, which is approximately square.

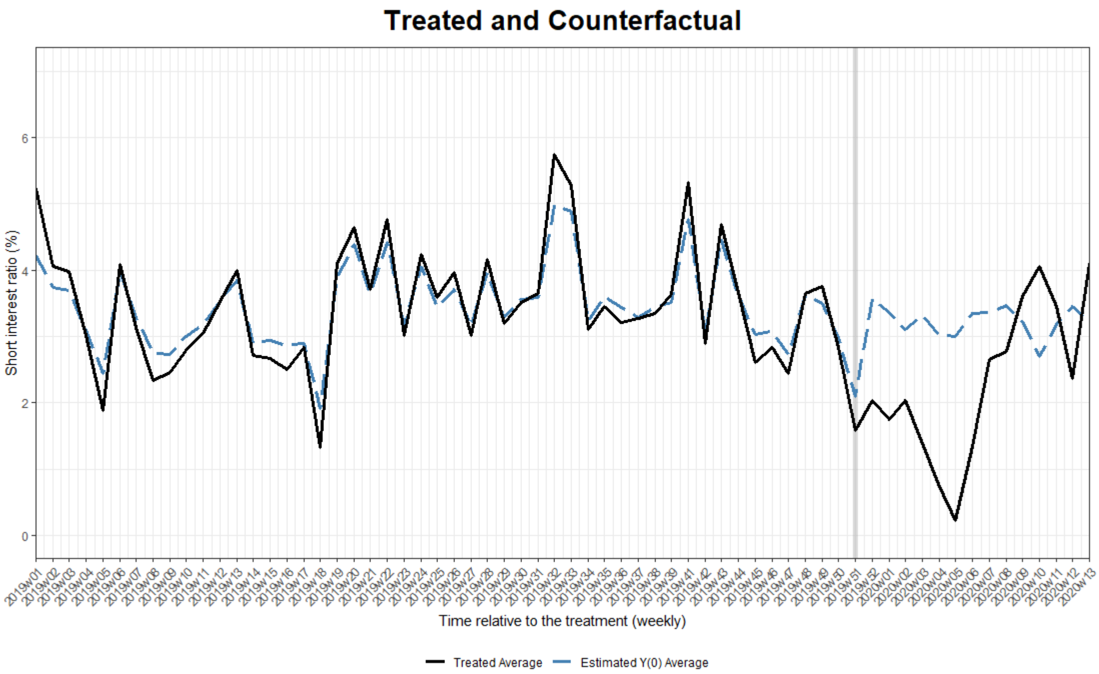
Figure 4.5: Treatment Status of Treated and Control ETFs



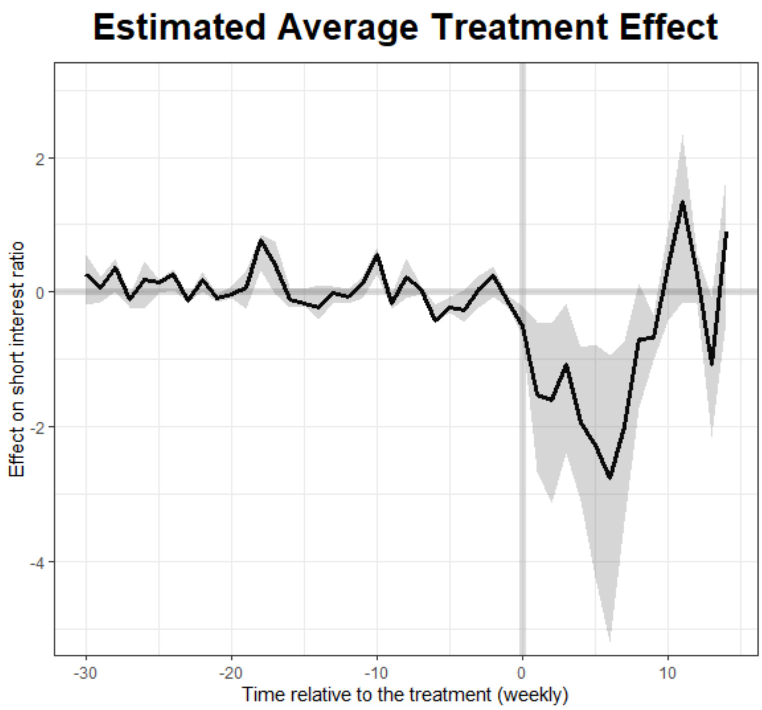
4.4 Empirical Results

After introducing ETF 300 options, the synthetic short interest ratio remains similar to before, but the actual observations present a transitory effect. Figure 4.6(a) plots

[6] Athey and Imbens (2018) say: "We find that the nuclear norm matrix completion estimator does well in a range of cases, including when T is small relative to N, when T is large relative to N, and when T and N are comparable. In contrast, the unconfoundedness and synthetic control approaches break down in some of these settings in the expected pattern (the unconfoundedness approach does not work very well if $T \gg N$, and the synthetic control approach does not work very well if $N \gg T$)."



(a)



(b)

Figure 4.6: Average Treatment Effect of Short Interest Ratio

the averaged actual short interest ratio of two treated ETFs and the counterfactual estimations. The blue dash line predicts treated ETFs, which assumes they have not been selected as targets of ETF 300 options. The dark solid line reflects the average short interest ratio of two treated ETFs and matches well with the blue line during the whole pre-treatment time. There is an obvious diverge point between two lines at 2% of short interest ratio in the first fifty weeks of 2019 (T_0). The actually observed ratio of treated ETFs witnesses a half-month fluctuation and sharp decline, reaching almost zero in the following four weeks. After the exhausting short selling in the equity market, the short interest ratio bounces back gradually and even exceeds 4% in the tenth week of 2020. By contrast, the counterfactual short interest ratio has an upward trend in the first week after the intervention and peaks at around 3.5%. The figure keeps around 3% in the following post-treatment time.

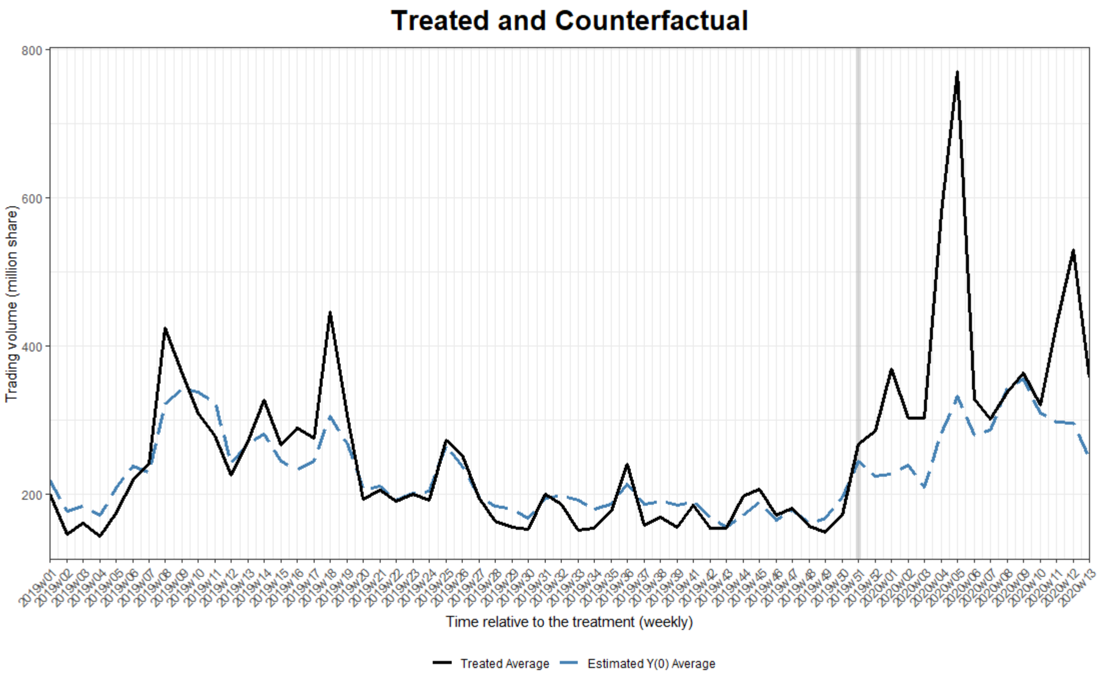
Figure 4.6(b) reflects the transitory treatment effect on short interest ratio with details, where the most significant negative effect is around −3% and the highest positive effect is over 1%. Nevertheless, the positive treatment effect is not significant. At the beginning of introducing the options, investors may establish their positions in the options market, and the number of short selling participants may not increase immediately. Therefore, short selling needs declines in the equity market in the first six weeks after introducing the options. Investors may switch to the options market at this stage, and the substitution effect would dominate in the equity lending market. Gradually, the short interest ratio increases to the level in the pre-treatment period, which supports the market completeness theory. Because investors may take bearish positions in the newly-listed options and then establish the short selling positions in the underlying market later, in this case, we would expect the short interest ratio in the underlying market to come back to the pre-treatment level and incorporates the options market.

Table 4.2 demonstrates the average treatment effect on short interest ratio and the p-value by period. The transitory treatment effect is significant with a 90% confidence interval, covering the first week of options introduction to the next eight weeks. Although Table 4.2 shows four weeks positive treatment effect and one week negative treatment effect on short selling ratio during post-treatment periods in the sample, it is not statistically significant. In the late stage, the unified and insignificant treatment estimation may be driven by gradually increased trading volume after the options listing and relevant stable needs of short selling. The short interest ratio is defined as the percentage of short selling shares divided by their trading volume. A possible interpretation is when the hedging and speculation needs are satisfied, the options market and the underlying market reach a balanced state. The shares of short selling become stable in the late stage of options listing, while the trading volume increases contentiously in the sample periods.

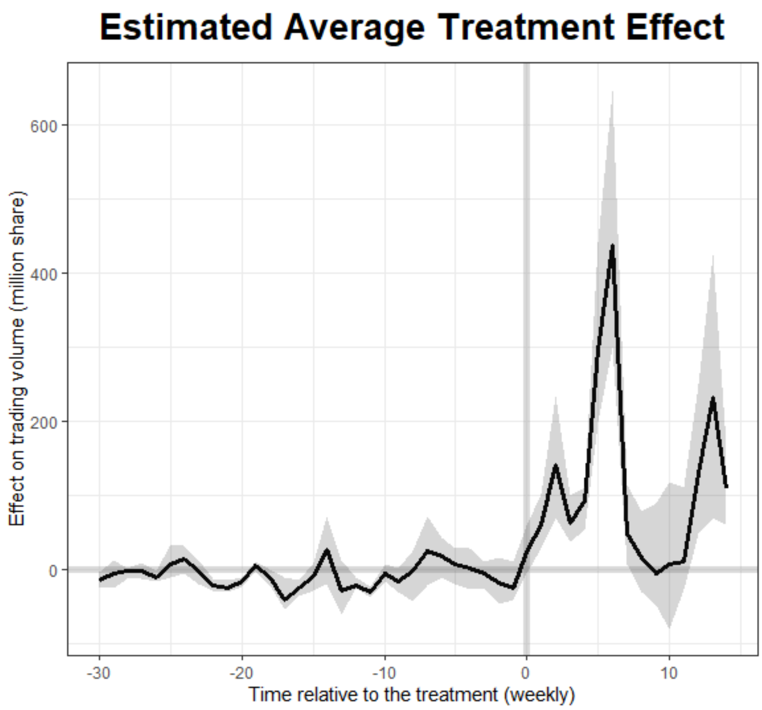
The options listing has -0.914% impact on the short interest ratio of two targeted ETFs on average. Compared with the Shenzhen market's -0.333% treatment effect, the Shanghai market ratio is almost five times lower. In the first row of Table 4.3 and Table 4.4, ETFs in both markets showed highly statistically significant negative estimation in the most post-treatment time. In sum, options introductions significantly negatively affect the short interest ratio in the underlying market during the sample periods. The transitory line of actual short interest ratio observation indicates that the options listing plays a complete market role in the equity market. The trading volume provides a more clear idea of the change of short interest ratio. Figure 4.7(a) compares the average trading volume of two targeted ETFs and the synthetic trading shares. Overall, there is a small gap between the trading volume of treated ETFs and the counterfactual trading volume before the ETF 300 options introductions. In contrast, the actual trading volume of treated ETFs has a much larger rising in the post-treatment stage. In January 2019, lower 200 million shares of treated ETFs are traded on average, while the trading volume peaks at just under 800 million shares in the fifth week of 2020.

The difference of treated and counterfactual trading volume is illustrated in Figure 4.7(b). The treatment effect for trading volume reaches the highest point at over 400 million shares around the sixth week after ETF 300 options introductions. Before the treatment effect rises to the second-highest shares, there is a temporary zero treatment effect around the tenth week after the intervention. The two treated ETFs have fluctuated treatment effect of trading volume after being targeted by ETF 300 options, but the overall effect is positive and significant over the period.

The second panel of Table 4.1 provides the results of the estimated treatment effect on



(a)



(b)

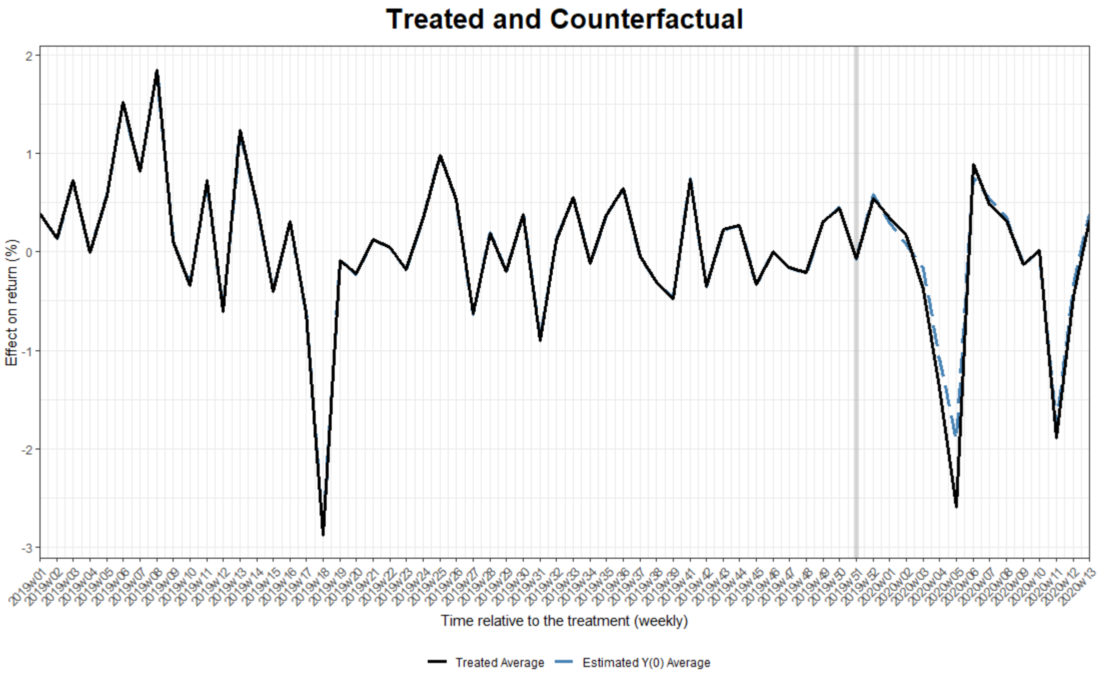
Figure 4.7: Average Treatment Effect of Trading Volume

ETFs trading volume. After the options announcement, the treated ETFs experience an increase in trading volume of 117.434 million shares on average. The ETF traded in the Shanghai market contributes the most liquidity improvement. The treatment difference in trading volume between the Shanghai and Shenzhen markets is as large as 46.845 million shares.

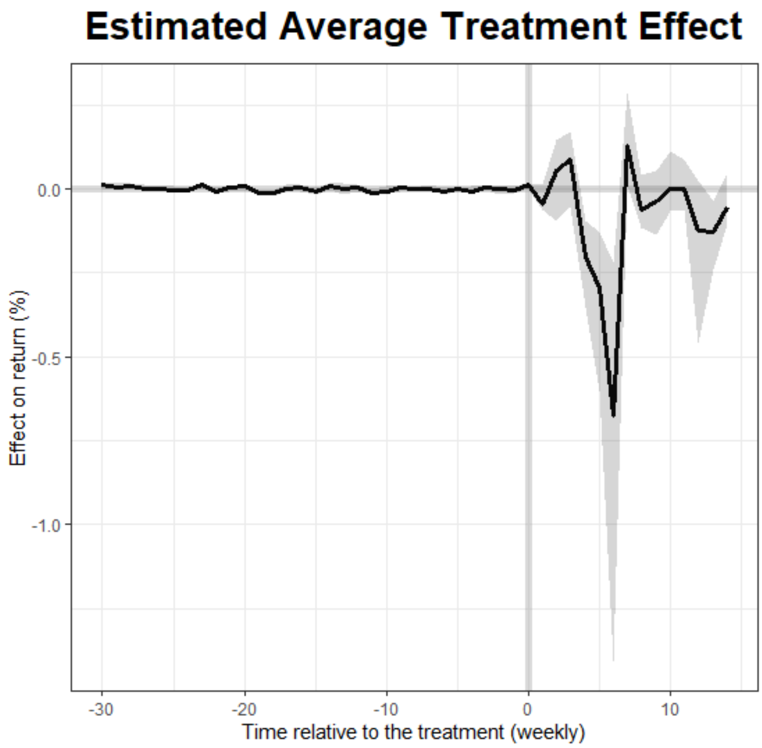
It is noticeable that the treated ETF in the Shenzhen market has a more stable treatment effect on trading volume than ETF in the Shanghai market and is highly statistically significant at 99% confidence interval except the tenth week of 2020. Compared with the consistent positive effect on liquidity in the Shenzhen market, the treatment effect of options introduction on the trading volume had three weeks negative influence on the targeted ETF in the Shanghai market. However, only the ninth week of 2020 shows a significant p-value at a 95% confidence interval. In sum, the two treated ETFs increase trading volume after the introduction of the options. However, their weekly treatment effect is different, and the ETF in the Shenzhen market has a consistent liquidity improvement significantly. A central argument about the influence of options on the stock market is that options release short selling constraints and complete the market. Apart from borrowing securities from dealers, investors can buy put options or sell call options alternatively. Thus, prices are expected to decline with fewer short selling costs and more available short selling opportunities. The return of two targeted ETFs declines after the options announcement, consisting of the short sale limitation theory (Miller, 1977).

However, the treatment effect on return is ambiguous and insignificant in the first two weeks after the event, and return declines significantly later. Figure 4.8(b) shows that the return of treated ETFs declines significantly at the third week after ETF 300 options introduction and reaches the lowest point at just over -0.75% around the 5th week of 2020. Besides, the negative treatment effect does not last in the long-term, which comes back to an average level around one week after the lowest record and keeps fluctuated later.

The return declines dramatically again in March 2020, but it may not be a pure reaction to the event of the option. The oil prices plummet in the international crude oil market and it causes a global stock market pandemic in March 2020. Figure



(a)



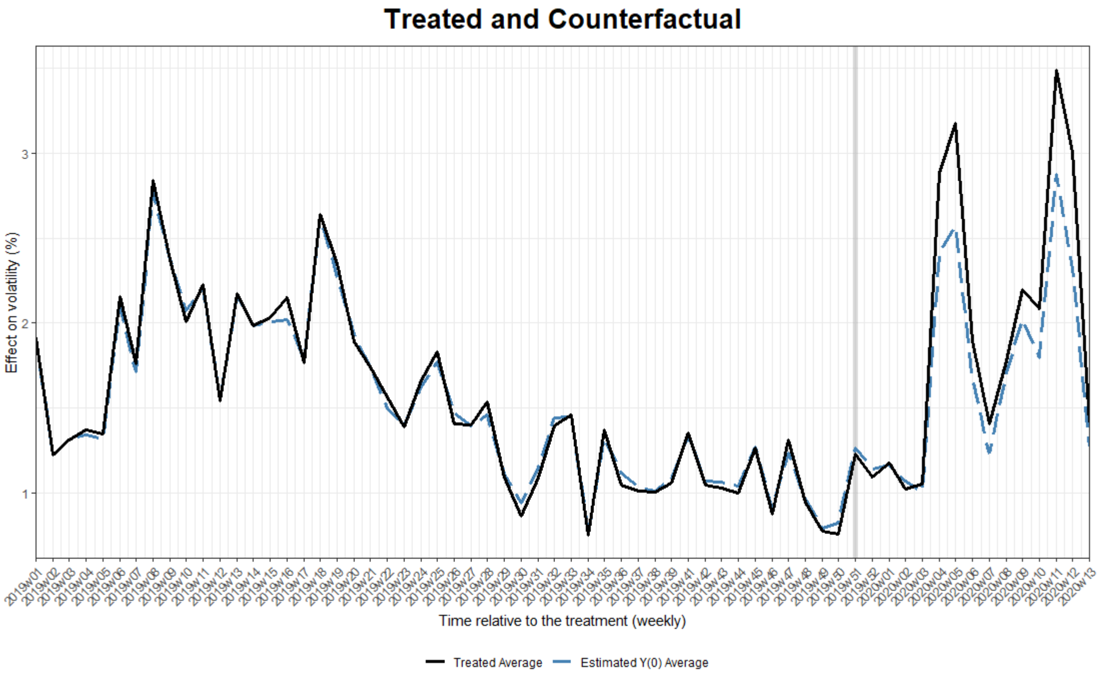
(b)

Figure 4.8: Average Treatment Effect of Return

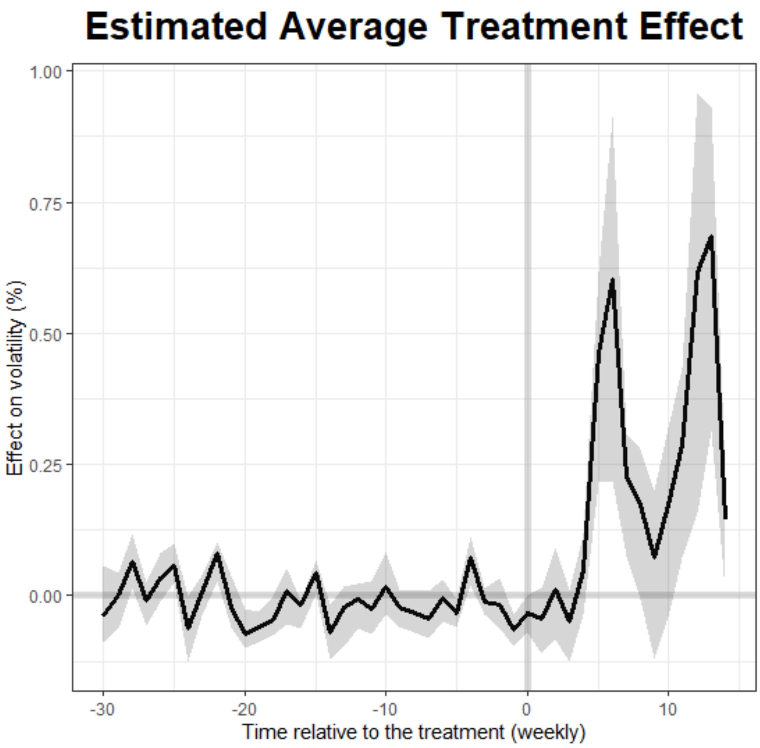
4.8(a) shows a second-lowest return in the 11th week of 2020, but there is no obvious difference between the observed return and the synthetic return. Figure 4.8(b) also illustrates small fluctuated treatment effect around that time. These results confirm that ETF options mitigate short selling constraints and decline the return of treated ETFs, but the short-term effect on return existed.

Because of the independence between Shanghai and Shenzhen stock exchange markets, short selling constraints in the two markets may differ, and the treatment effect on the return may not be unified. The overall treatment effect on return in the first quarter after options introductions is −0.097%. The ETF traded in the Shenzhen market has −0.085% return decline, more than twofold of the one traded in the Shanghai market. The third row Table 4.3 and Table 4.4 show that the treatment effect by the Shenzhen market period is less significant and declines more in return over the most post-treatment time. The p-value of the overall return treatment effect is smaller than 0.05 from the fourth week to the seventh week after options introduction, which means a significant and around one month negative impact on treated ETFs return after introducing the options. In Figure 4.9(a), both actual treated average and estimated synthetic average volatility rate rise over the post-treatment period, but the figures for treated ETFs are significantly higher. There is a relevant stable trend of volatility in the second half-year of 2019, under 1.5%. Besides, the volatility of control ETFs and treated ETFs has no significant changes in trend during the pre-treatment periods. These indicate that there is no pre-trend before the options announcement. It is noticeable that volatility reaches over 3% in the post-treatment periods, which corresponds to spikes in return at the same time. Therefore, the rising in volatility is not necessarily driven by option introduction entirely. It may come from overvalued prices, which is a reasonable reaction to market efficiency improvement.

Figure 4.9(b) reports the net difference of observed and synthetic volatility. Because the synthetic volatility matches well with the actual volatility rate, there is an ideal zero treatment effect before intervention ($-30 < t < 0$). The first five weeks after the event, the two treated ETFs react to ETF 300 option introduction news with a jump of around 0.6% concerning volatility and peaked at over 0.6% in the eleventh week of 2020. The options introductions event increased the volatility of treated ETFs,



(a)



(b)

Figure 4.9: Average Treatment Effect of Volatility

and the treatment effect remained even eleven weeks after the event.

Table 4.1 and Table 4.2 formalise the information and provide in Figure 4.9. In the last three columns of Table 4.1, there is extra volatility of 0.244% between the actual observed volatility and counterfactual volatility during the post-treatment periods. The treated ETF in Shenzhen Stock Exchange has a higher treatment effect than the one in Shanghai Stock Exchange, which is 0.266% and 0.194%, respectively.

The ETF 300 options introductions stimulate both treated ETFs' volatility over observed time, but this treatment effect is only significant around two high volatility periods. The last row of Table 4.2 reports the weekly treatment effect on volatility. There are two insignificant negative treatment effects at the 52nd week of 2019 (T_0) and the second week of 2020, while the rest of the weekly treatment effect show positive estimations. The last row of Table 4.3 and Table 4.4 shows the weekly treatment effect of volatility on two treated ETFs, respectively. Besides, both ETFs have the same treatment trend in each period, but figures in Shanghai Stock Exchange are less significant than the one traded in the Shenzhen market.

Table 4.1: Main Results of Generalized Synthetic Control

	Short interest			Trading volume			Return			Volatiity		
	(all)	(Shanghai)	(Shenzhen)	(all)	(Shanghai)	(Shenzhen)	(all)	(Shanghai)	(Shenzhen)	(all)	(Shanghai)	(Shenzhen)
Treatment	-0.914	-1.478	-0.333	117.434	144.064	97.219	-0.097	-0.038	-0.085	0.244	0.194	0.266
(S.E)	(0.41)	(0.13)	(0.10)	(19.01)	(10.76)	(10.76)	(0.04)	(0.01)	(0.04)	(0.05)	(0.05)	(0.05)
CI.lower	-1.710	-1.802	-0.604	86.810	111.820	88.587	-0.190	-0.060	-0.168	0.110	0.075	0.129
CI.upper	-0.330	-1.357	-0.266	188.990	180.448	128.947	-0.040	-0.018	-0.027	0.320	0.259	0.319
Lambda	3.159	7.484	7.356	471.944	471.770	467.864	0.100	0.237	0.100	0.598	0.596	0.596
Treated	2	1	1	2	1	1	2	1	1	2	1	1
Control	42	42	42	42	42	42	42	42	42	42	42	42

Table 4.2: Average Treatment Effect by Period

Period	2019w51	2020w1	2020w2	2020w3	2020w4	2020w5	2020w6	2020w7	2020w8	2020w9	2020w10	2020w11	2020w12	2020w13
Short interest	-1.537	-1.606	-1.076	-1.935	-2.279	-2.775	-2.005	-0.711	-0.687	0.378	1.348	0.271	-1.079	0.897
p.value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.094*	*0.000*	*0.518*	*0.226*	*0.428*	*0.026*	*0.356*
Trading volume	60.201	142.309	63.228	93.455	296.577	438.861	48.036	15.538	-5.861	7.877	10.922	130.552	233.134	109.243
p.value	*0.016*	*0.000*	*0.004*	*0.000*	*0.000*	*0.000*	*0.040*	*0.326*	*0.750*	*0.686*	*0.362*	*0.000*	*0.000*	*0.000*
Return	-0.044	0.054	0.087	-0.205	-0.295	-0.676	0.128	-0.065	-0.040	0.000	-0.002	-0.123	-0.128	-0.055
p.value	*0.170*	*0.828*	*0.346*	*0.000*	*0.002*	*0.002*	*0.036*	*0.234*	*0.418*	*0.640*	*0.654*	*0.108*	*0.006*	*0.382*
Volatility	-0.043	0.012	-0.050	0.048	0.463	0.604	0.228	0.175	0.074	0.174	0.287	0.615	0.685	0.145
p.value	*0.138*	*0.936*	*0.090*	*0.370*	*0.000*	*0.000*	*0.000*	*0.094*	*0.598*	*0.118*	*0.004*	*0.002*	*0.000*	*0.032*

Table 4.3: Treatment Effect by Period (Shanghai)

Period	2019w51	2020w01	2020w02	2020w03	2020w04	2020w05	2020w06	2020w07	2020w08	2020w09	2020w10	2020w11	2020w12	2020w13
Short interest	-2.454	-2.689	-2.182	-3.056	-3.782	-4.658	-3.279	-1.532	-0.777	0.913	2.493	0.485	-1.792	1.613
p.value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.194*	*0.000*	*0.000*
Trading volume	51.193	212.210	62.190	85.211	396.398	578.582	16.487	-10.938	-34.335	-68.802	19.354	197.540	375.608	136.202
p.value	*0.083*	*0.000*	*0.042*	*0.042*	*0.000*	*0.000*	*0.375*	*0.750*	*0.375*	*0.042*	*0.458*	*0.000*	*0.000*	*0.000*
Return	-0.011	0.097	0.003	-0.101	-0.109	-0.265	0.083	-0.033	-0.015	-0.023	0.027	-0.124	-0.036	-0.029
p.value	*0.407*	*0.034*	*0.847*	*0.000*	*0.000*	*0.000*	*0.034*	*0.169*	*0.407*	*0.847*	*0.068*	*0.000*	*0.305*	*0.373*
Volatility	-0.036	0.009	-0.003	0.024	0.382	0.394	0.260	0.207	0.027	0.080	0.335	0.369	0.526	0.137
p.value	*0.258*	*0.806*	*0.581*	*0.516*	*0.000*	*0.065*	*0.000*	*0.065*	*0.968*	*0.355*	*0.000*	*0.065*	*0.000*	*0.032*

Table 4.4: Treatment Effect by Period (Shenzhen)

Period	2019w51	2020w1	2020w2	2020w3	2020w4	2020w5	2020w6	2020w7	2020w8	2020w9	2020w10	2020w11	2020w12	2020w13
Short interest	-0.475	-0.515	-0.298	-0.983	-0.951	-1.150	-0.769	0.019	-0.465	-0.126	0.416	0.283	0.024	0.329
p.value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.440*	*0.000*	*0.000*	*0.214*	*0.500*	*0.452*	*0.905*
Trading volume	72.818	76.722	68.253	104.846	202.259	305.497	84.536	46.652	32.025	94.150	11.875	72.870	99.775	88.783
p.value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.070*	*0.000*	*0.000*	*0.000*
Return	-0.065	0.007	0.103	-0.172	-0.304	-0.385	0.063	-0.081	-0.047	-0.018	-0.036	-0.021	-0.151	-0.078
p.value	*0.000*	*0.761*	*0.323*	*0.013*	*0.000*	*0.245*	*0.413*	*0.065*	*0.490*	*0.916*	*0.387*	*0.981*	*0.000*	*0.065*
Volatility	-0.038	0.011	-0.089	0.073	0.485	0.682	0.174	0.154	0.114	0.238	0.231	0.772	0.779	0.136
p.value	*0.228*	*0.975*	*0.000*	*0.051*	*0.000*	*0.000*	*0.013*	*0.051*	*0.266*	*0.000*	*0.038*	*0.000*	*0.000*	*0.101*

4.4.1 Comparison with Difference-in-Differences Results

This section applies the DiD method to explore the treatment effect on short interest, liquidity, return, and volatility in the treated group and compares these treatment estimations with the generalized synthetic control method results. Table 4.5 provides the results of a multivariate regression analysis within the short selling sample involved ETFs. The DiD estimation follows the panel data regression:

$$Y_{it} = c + \beta_1 * ETF_i + \beta_2 * time_t + \beta_3 * ETF_i * time_t + \varepsilon_i \tag{4.20}$$

The dependent variable represents the short interest ratio, trading volume, return, and volatility for each ETF each week between the first week of 2019 to the last week of March in 2020. β_3 is the key parameter, which captures the treatment effect. The unit dummy variable is ETF_i, which equals 1 if the unit belongs to the treated group. Similarly, $time_t$ is the post-treatment time indicator, which equals 0 if earlier than the intervention time t_0 (2019 week 52th). The interactive term equals to 1 only if both ETF_i and $time_t$ equal to 1.

Column (1) of Table 4.5 is the short interest ratio regression without any fixed effect control, and column (2) controls the individual effect. Although the treatment effect shows the statistically significant and negative estimation in all short interest regressions, the regression (3) with both individual and time effect control has the highest R-square value. After controlling both effects, the coefficient of the interaction term between the ETFs dummy and post-treatment time dummy is −2.105, which means there is a decline of 2.105% in total short selling interest ratio for those treated ETFs in the 14 weeks following the options announcement.

However, the short interest treatment parameter in the generalized synthetic control method is −0.914, which is about half as the coefficient estimated by the DiD method. Figure 4.6 plots a highly volatile short interest ratio of treated ETFs before the option event while the control group shows a very stable level at the same period. Therefore, the biased negative treatment effect of the DiD method is probably due to the unparalleled trend of short selling ratio between the treated and control groups.

The coefficient of return treatment is negative in two different methods. Regression

Table 4.5: Results of Difference in Differences

	Short interest			Trading volume			Return			Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	-2.021***	-2.087***	-2.105***	112.809*	111.485*	112.928*	-0.097***	-0.105***	-0.067**	-0.218***	-0.214***	-0.197**
(S.E)	(-4.02)	(-4.14)	(-4.09)	(2.43)	(2.39)	(2.38)	(-4.30)	(-4.47)	(-3.14)	(-3.69)	(-3.73)	(-3.43)
Time	0.893*	0.959*		68.859*	70.182*		-0.291***	-0.283***		0.688***	0.684***	
(S.E)	(2.43)	(2.60)		(2.12)	(2.14)		(-12.93)	(-12.01)		(13.16)	(13.54)	
ETF	3.008			105.378			0.025*			-0.294***		
(S.E)	(1.85)			(1.01)			(2.29)			(-4.94)		
_cons	0.441*	0.570***	0.782***	111.008**	115.740***	131.211***	0.095***	0.094***	0.031***	1.801***	1.788***	1.938***
(S.E)	(2.57)	(7.34)	(146.08)	(3.33)	(16.78)	(266.27)	(8.61)	(18.99)	(139.91)	(30.27)	(168.13)	(3247.27)
N	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692	2692
R-sq	0.079	0.428	0.464	0.023	0.738	0.757	0.018	0.025	0.822	0.094	0.275	0.794

* p¡0.05, ** p¡0.01, *** p¡0.001

(7) in Table 4.5 without fixed effect control exhibit a 0.097% declined return in the treated group after the options scheme, comparing with non-treated ETFs with 99% confidence interval and 0.018 R-square. Regression (8) controls both individual and time effects and shows −0.067% return decline with 90% confidence interval. The p-value about return treatment would be less significant if the post-treatment time is longer, because the negative influence on return is short-term existed.

The treatment effect of ETF liquidity is obvious and significant at 95% confidence interval by the DiD method. Column (6) in Table 4.5 has better model fitting than regressions without individual and time control. The treatment effect of options introduction on ETFs' trading volume shows similar results by generalized synthetic control and DiD method, 117.434 million and 112.928 million, respectively. The coefficient difference scale indicates that the obey of common trend assumption, which also consists of a similar trend in Figure 4.7.

The volatility analysis of DiD provides opposite results with the generalized synthetic control method with matrix completion estimation. The last column of Table 4.5 displays a 0.197% decrease of the volatility of the treated group over the post-treatment time, which has a 90% confidence interval and 0.794 R-square. By contrast, the volatility of the treated group increases 0.244% after the options announcement by the generalized synthetic control method. But results in Table 4.2 and Table 4.3 suggest that the positive treatment effect is not significant during the most post-treatment periods, especially in the Shanghai market. The averaged time series of volatility follows a similar movement in the treated and control groups during the sample period. This is in line with the fact that the DiD method provides better results than the generalized synthetic control method with matrix completion estimation in this case.

4.5 Conclusion

I examined the SCI 300 ETF options introductions' impact on their targeted ETFs. Applying the generalized synthetic control method, I found that the estimated average treatment effect on the short interest ratio declined in the short run, and decreased return rates were also transitory. But the trading volume of treated ETFs was positively related to options listing during the whole sample period. These results were consistent with the coefficients sign of DiD method, while treatment magnitudes showed significant differences if the parallel trend assumption was violated. Except for the ambiguous and opposite volatility results, both methods reported statistically substantial treatment effect estimations.

Shanghai Stock Exchanges illustrated a more obvious treatment effect than Shenzhen Stock Exchanges in terms of short interest ratio and trading volume. Simultaneously, the treated ETF in the Shenzhen market contributed the most negative impact of return rates over post-treatment periods. It indicated that the SCI 300 ETF traded in the Shanghai market was more active and efficient than the one in the Shenzhen market.

On average, the whole treated ETFs had a -0.914% decline in short interest ratio, 117.434 million shares increase of trading volume, and -0.097% decrease of return during post-treatment sample periods. The CSI 300 ETF options introductions improved the overall quality of the underlying ETFs.

Appendix A

Table 4.A1: Treated and Control ETFs

Ticker	Launch date	Tracking index	Market
Treated			
159919	2012-05-07	CSI 300 Index	Shenzhen
510300	2012-05-04	CSI 300 Index	Shanghai
Controll			
159901	2006-03-24	Shenzhen Stock Exchange 100 Index (Price)	Shenzhen
159902	2006-06-08	Small and Medium Board Index (price)	Shenzhen
159905	2010-11-05	SZSE Dividend Price Index	Shenzhen
159910	2011-08-01	Shenzhen F120 Index	Shenzhen
159915	2011-09-20	Growth Enterprise Index (Price)	Shenzhen
159922	2013-02-06	CSI 500 Index	Shenzhen
159925	2013-02-18	CSI 300 Index	Shenzhen
159928	2013-08-23	CSI Consumer Staples Index	Shenzhen
159938	2014-12-01	CSI All Share Health Care Index	Shenzhen
159939	2015-01-08	CSI All Share Information Technology Index	Shenzhen
159948	2016-05-13	ChiNext Index (Price)	Shenzhen
159949	2016-06-30	ChiNext 50 Index	Shenzhen
159952	2017-04-25	ChiNext Index (Price)	Shenzhen
159959	2018-10-22	CSI Central Enterprises Structure Adjustment Index	Shenzhen
510160	2010-08-27	China Security Southern Well-off Industry Index	Shanghai
510180	2006-04-13	SSE 180 Index	Shanghai
510230	2011-03-31	Shanghai Stock Exchange 180 Financial Index	Shanghai
510310	2013-03-06	CSI 300 Index	Shanghai
510330	2012-12-25	CSI 300 Index	Shanghai
510390	2017-12-25	CSI 300 Index	Shanghai
510500	2013-02-06	CSI 500 Index	Shanghai
510510	2013-04-11	CSI 500 Index	Shanghai
510590	2018-03-23	CSI 500 Index	Shanghai
510710	2015-05-27	SSE 50 Index	Shanghai
510810	2016-07-28	CSI Shanghai State-owned Enterprises Index	Shanghai
510850	2018-12-07	SSE 50 Index	Shanghai
510880	2006-11-17	SSE Dividend Index	Shanghai
510900	2012-08-09	Hang Seng China Enterprises Index	Shanghai
512000	2016-08-30	CSI All Index Securities Company Index	Shanghai
512010	2013-09-23	CSI 300 Medical and Health Index	Shanghai
512070	2014-06-26	CSI 300 Non-Bank Financial Index	Shanghai
512090	2018-05-17	MSCI China A Shares International Link Index	Shanghai
512160	2018-04-03	MSCI China A Shares International Link Index	Shanghai
512180	2018-04-19	MSCI China A Shares International Link Index	Shanghai
512500	2015-05-05	CSI 500 Index	Shanghai
512580	2017-01-25	China Securities Environmental Industry Index	Shanghai
512660	2016-07-26	China Securities Military Index	Shanghai
512800	2017-07-18	China Securities Bank Index	Shanghai
512880	2016-07-26	CSI All Index Securities Company Index	Shanghai
512900	2017-03-10	CSI All Index Securities Company Index	Shanghai
512950	2018-10-19	China Securities Central Enterprise Structure Adjustment Index	Shanghai
512980	2017-12-27	China Securities Media Index	Shanghai

Chapter 5

Conclusion

5.1 Summary of Findings

This thesis examined the impact of consecutive reverse repo, the lifting of margin trading and short selling bans, and options introductions on Chinese ETFs market. Chapter 2 found that the capital liquidity released by reverse repo had insignificant improvement of ETFs mispricing. I applied synthetic control methods in financial market design for chapter 3 and chapter 4, and compared results with the commonly used DiD method. ETFs with margin trading and short selling qualification improved ETFs trading volume significantly, while treatment effect of return and volatility was ambiguous. Similarly, the introductions of ETFs options improved ETFs trading volume, declined short interest ratio and return, while the treatment effect did not exist for a long time, which indicated a complementary effect between the option market and the underlying market. Both chapters reported unclear results on ETFs volatility, which inspired my further thinking about modifying the synthetic control model for a more general application in financial market.

5.2 Suggestions for Future Research

There are two main considerations when estimating the causal impact of policy or events on financial market. Firstly, the number of control units and the similarities with treated units should be carefully considered. Although several recent proposed synthetic control methods (Ben-Michael et al., 2021; Xu, 2017) have allowed negative weights assignment to control units, we still need to pay attention to the control units with negative weights to avoid the over-fitting problem. Secondly, researchers may get an over-dispersed weight matrix if too many control units or the pre-treatment time cover the financial crisis.

The current representative synthetic control methods (Abadie et al., 2010, 2015; Abadie and Gardeazabal, 2003; Liu et al., 2020; Xu, 2017) usually estimate a small sample causal effect with low data frequency, limiting its application on long time series samples, but empirical financial studies usually have high-frequency and unbalanced data with missing values. There are two critical challenges for a more general application in financial market: 1) how to select different synthetic control methods on different financial market designs, 2) how to improve the synthetic generation process accuracy under a large data set.

Compared with traditional synthetic control estimation methods with different weight assignments of control units, matrix completion treats elements of the control outcome matrix as missing values. We need to find a matrix with the smallest number of ranks with the smallest gap to the part of the outcome matrix that is not missing. Netflix company successfully extrapolates the ratings of the entire user base for different movies from a very sparse set of existing data (Koren, 2009). Athey et al. (2021) discuss matrix completion application for causal panel data models, which further supports the practicality of this research plan. This estimation method might work well in variables with obvious trending such as trading volume. Similarly, the users' favorite movie categories usually have trends in the Netflix example. There would be a wide application in large and high-frequency finance databases after a further combination of matrix completion and synthetic control idea.

One of the essential financial variables–volatility may not have a highly accurate and significant treatment effect estimation by current synthetic control methods. Alternatively, we could introduce autoregressive conditional heteroskedasticity (ARCH) models (Engle, 1982) and generalized autoregressive conditional heteroskedasticity (GARCH) models (Bollerslev, 1986) to the synthetic estimation process. Furthermore, spatial ARCH (S-ARCH) and spatial AGRCH models (Sato and Matsuda, 2017, 2021) could provide effective tools to investigate cross-market and multiple markets volatilities. The first step is using treated observations before intervention in S-GARCH model and generating outcomes. Next, we construct synthetic control data in the same period by assigning different weights for different control units and acquire synthetic outcomes. The weights should keep the closed gap between actual outcomes and synthetic outcomes. The final step is using the weights to construct counterfactuals over post-treatment time.

As the considerations mentioned above, if the pre-treatment covers abnormal periods such as financial crisis, the synthetic process might generate poorly. We could use S-GARCH models to express volatility clustering and spillover effect between treated group and control group, rather than choose another pre-treatment period. Researchers could have an alternative empirical tool to analyze volatility and asset pricing, particularly in the futures market. For instance, the rotation of dominant futures in different months or seasons are natural intervention points, and we could use the contemporaneous sub-dominate futures as a control group. It would be inspiring to construct counterfactuals and predict the short-term volatility violation caused by the rotation of dominant futures.

In sum, it is possible to analyze short-term market performance prediction under a more accurate synthetic generation process based on a high-frequency time series sample, such as futures volatility and asset pricing.

Bibliography

Abadie, A., Diamond, A. and Hainmueller, J. (2010), 'Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program', *Journal of the American statistical Association* **105**(490), 493–505.

Abadie, A., Diamond, A. and Hainmueller, J. (2015), 'Comparative politics and the synthetic control method', *American Journal of Political Science* **59**(2), 495–510.

Abadie, A. and Gardeazabal, J. (2003), 'The economic costs of conflict: A case study of the basque country', *American economic review* **93**(1), 113–132.

Aber, J. W., Li, D. and Can, L. (2009), 'Price volatility and tracking ability of etfs', *Journal of Asset Management* **10**(4), 210–221.

Abraham, S. and Sun, L. (2018), 'Estimating dynamic treatment effects in event studies with heterogeneous treatment effects', *Available at SSRN* **3158747**.

Ackert, L. F., Charupat, N., Church, B. K. and Deaves, R. (2006), 'Margin, short selling, and lotteries in experimental asset markets', *Southern Economic Journal* **73**(2), 419–436.

Ackert, L. F. and Tian, Y. S. (2008), 'Arbitrage, liquidity, and the valuation of exchange traded funds', *Financial markets, institutions & instruments* **17**(5), 331–362.

Adrian, T. and Shin, H. S. (2008), 'Liquidity, monetary policy, and financial cycles', *Current issues in economics and finance* **14**(1).

Agapova, A. (2011), 'Conventional mutual index funds versus exchange-traded funds', *Journal of Financial Markets* **14**(2), 323–343.

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of financial markets* **5**(1), 31–56.

Amjad, M., Shah, D. and Shen, D. (2018), 'Robust synthetic control', *The Journal of Machine Learning Research* **19**(1), 802–852.

Anufriev, M. and Tuinstra, J. (2013), 'The impact of short-selling constraints on financial market stability in a heterogeneous agents model', *Journal of Economic Dynamics and Control* **37**(8), 1523–1543.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W. and Wager, S. (2019), Synthetic difference in differences, Technical report, National Bureau of Economic Research.

Arkorful, G. B., Chen, H., Liu, X. and Zhang, C. (2020), 'The impact of options introduction on the volatility of the underlying equities: evidence from the chinese stock markets', *Quantitative Finance* **20**(12), 2015–2024.

Aronow, P. M. and Samii, C. (2017), 'Estimating average causal effects under general interference, with application to a social network experiment', *The Annals of Applied Statistics* **11**(4), 1912–1947.

Asness, C. (2004), *Short selling: strategies, risks, and rewards*, John Wiley & Sons.

Asquith, P., Pathak, P. A. and Ritter, J. R. (2005), 'Short interest, institutional ownership, and stock returns', *Journal of Financial Economics* **78**(2), 243–276.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G. and Khosravi, K. (2021), 'Matrix completion methods for causal panel data models', *Journal of the American Statistical Association* **116**(536), 1716–1730.

Athey, S. and Imbens, G. (2016), 'Recursive partitioning for heterogeneous causal effects', *Proceedings of the National Academy of Sciences* **113**(27), 7353–7360.

Athey, S. and Imbens, G. W. (2017), 'The state of applied econometrics: Causality and policy evaluation', *Journal of Economic Perspectives* **31**(2), 3–32.

Athey, S. and Imbens, G. W. (2018), Design-based analysis in difference-in-differences settings with staggered adoption, Technical report, National Bureau of Economic Research.

Ausubel, L. M. (1990), ‘Insider trading in a rational expectations economy’, *The American Economic Review* pp. 1022–1041.

Bai, J. (2009), ‘Panel data models with interactive fixed effects’, *Econometrica* **77**(4), 1229–1279.

Bai, J. and Ng, S. (2002), ‘Determining the number of factors in approximate factor models’, *Econometrica* **70**(1), 191–221.

Ben-Michael, E., Feller, A. and Rothstein, J. (2021), ‘The augmented synthetic control method’, *Journal of the American Statistical Association* **116**(536), 1789–1803.

Benkwitz, A., Neumann, M. H. and Lütekpohl, H. (2000), ‘Problems related to confidence intervals for impulse responses of autoregressive processes’, *Econometric Reviews* **19**(1), 69–103.

Bernanke, B. S. and Gertler, M. (2000), ‘Monetary policy and asset price volatility’.

Bhojraj, S., Bloomfield, R. J. and Tayler, W. B. (2009), ‘Margin trading, overpricing, and synchronization risk’, *The Review of Financial Studies* **22**(5), 2059–2085.

Black, F. and Scholes, M. (1973), ‘The pricing of options and corporate liabilities’, *Journal of political economy* **81**(3), 637–654.

Blackwell, M. and Glynn, A. N. (2018), ‘How to make causal inferences with time-series cross-sectional data under selection on observables’, *American Political Science Review* **112**(4), 1067–1082.

Blanchard, O. and Fischer, S. (1989), *Lectures on macroeconomics*, MIT press.

Blanchard, O. J. (1981), ‘Output, the stock market, and interest rates’, *The American Economic Review* **71**(1), 132–143.

Blau, B. M. and Wade, C. (2013), ‘Comparing the information in short sales and put options’, *Review of Quantitative Finance and Accounting* **41**(3), 567–583.

Blitz, D., Huij, J. and Swinkels, L. (2012), 'The performance of european index funds and exchange-traded funds', *European Financial Management* **18**(4), 649–662.

Bloom, N., Bond, S. and Van Reenen, J. (2007), 'Uncertainty and investment dynamics', *The review of economic studies* **74**(2), 391–415.

Bollen, N. P. (1998), 'A note on the impact of options on stock return volatility', *Journal of banking & Finance* **22**(9), 1181–1191.

Bollerslev, T. (1986), 'Generalized autoregressive conditional heteroskedasticity', *Journal of econometrics* **31**(3), 307–327.

Bordo, M. D. and Jeanne, O. (2002), 'Boom-busts in asset prices, economic instability, and monetary policy'.

Brunnermeier, M. K. and Pedersen, L. H. (2009), 'Market liquidity and funding liquidity', *The review of financial studies* **22**(6), 2201–2238.

Callen, J. L. and Fang, X. (2015), 'Short interest and stock price crash risk', *Journal of Banking & Finance* **60**, 181–194.

Canakgoz, N. A. and Beasley, J. E. (2009), 'Mixed-integer programming approaches for index tracking and enhanced indexation', *European Journal of Operational Research* **196**(1), 384–399.

Chan, K., Kot, H. W. and Yang, Z. (2010), 'Effects of short-sale constraints on stock prices and trading activity: Evidence from hong kong and mainland china', *Available at SSRN 1572067* .

Chang, E. C., Cheng, J. W. and Yu, Y. (2007), 'Short-sales constraints and price discovery: Evidence from the hong kong market', *The Journal of Finance* **62**(5), 2097–2121.

Chang, E. C., Luo, Y. and Ren, J. (2012), 'Costly and unprofitable speculation: evidence from trend-chasing chinese short-sellers and margin-traders', *Social Science Research Network* .

Chang, E. C., Luo, Y. and Ren, J. (2014), 'Short-selling, margin-trading, and price efficiency: Evidence from the chinese market', *Journal of Banking & Finance* **48**, 411–424.

Charoenrook, A. and Daouk, H. (2009), A study of market-wide short-selling restrictions, Technical Report 642-2016-44312, Cornell University.

Chen, C. X. and Rhee, S. G. (2010), 'Short sales and speed of price adjustment: Evidence from the hong kong stock market', *Journal of Banking & Finance* **34**(2), 471–483.

Chen, D.-H. and Chang, P.-H. (2008), 'The impact of listing stock options on the underlying securities: the case of taiwan', *Applied financial economics* **18**(14), 1161–1172.

Chen, H., Chow, K. and Tillmann, P. (2017), 'The effectiveness of monetary policy in china: Evidence from a qual var', *China Economic Review* **43**, 216–231.

Chen, J., Li, H. and Zheng, D. (2020), 'The impact of margin-trading and short-selling on stock price efficiency—evidence from the fifth-round ban lift in the chinese stock market', *The Chinese Economy* **53**(3), 265–284.

Chen, T., Wong, K. H., Susai, M. et al. (2016), 'Active management and price efficiency of exchange-traded funds', *Prague Economic Papers* **25**(1), 3–18.

Chernozhukov, V., Wüthrich, K. and Zhu, Y. (2021), 'An exact and robust conformal inference method for counterfactual and synthetic controls', *Journal of the American Statistical Association* **116**(536), 1849–1864.

Chou, R. K., Wang, G. H. and Wang, Y.-Y. (2015), 'The effects of margin changes on the composition of traders and market liquidity: Evidence from the taiwan futures exchange', *Journal of Futures Markets* **35**(10), 894–915.

Chowdhry, B. and Nanda, V. (1998), 'Leverage and market stability: The role of margin rules and price limits', *The Journal of Business* **71**(2), 179–210.

Copeland, A., Duffie, D., Martin, A. and McLaughlin, S. (2012), 'Key mechanics of the us tri-party repo market', *Federal Reserve Bank of New York Economic Policy Review* **18**(3), 17–28.

Danielson, B. R. and Sorescu, S. (2001), 'Why do option introductions depress stock prices', *A Study of Diminishing Short-Sale Constraints. DePaul University and University of Houston Working Paper* .

Daouk, H. and Charoenrook, A. A. (2005), 'A study of market-wide short-selling restrictions', *Available at SSRN 687562* .

Datar, V. T., Naik, N. Y. and Radcliffe, R. (1998), 'Liquidity and stock returns: An alternative test', *Journal of Financial Markets* **1**(2), 203–219.

David, H. (2018), *Price and Financial Stability: Rethinking Financial Markets*, Routledge.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020), 'Two-way fixed effects estimators with heterogeneous treatment effects', *American Economic Review* **110**(9), 2964–96.

Dechow, P. M., Hutton, A. P., Meulbroek, L. and Sloan, R. G. (2001), 'Short-sellers, fundamental analysis, and stock returns', *Journal of financial Economics* **61**(1), 77–106.

Deng, X. and Gao, L. (2018), 'The monitoring of short selling: Evidence from china', *Research in International Business and Finance* **43**, 68–78.

Desai, H., Ramesh, K., Thiagarajan, S. R. and Balachandran, B. V. (2002), 'An investigation of the informational role of short interest in the nasdaq market', *The Journal of Finance* **57**(5), 2263–2287.

Diamond, D. W. and Verrecchia, R. E. (1987), 'Constraints on short-selling and asset price adjustment to private information', *Journal of Financial Economics* **18**(2), 277–311.

Diether, K. B., Lee, K.-H. and Werner, I. M. (2009), 'Short-sale strategies and return predictability', *The Review of Financial Studies* **22**(2), 575–607.

Doudchenko, N. and Imbens, G. W. (2016), Balancing, regression, difference-in-differences and synthetic control methods: A synthesis, Technical report, National Bureau of Economic Research.

Edwards, S. and Susmel, R. (2001), 'Volatility dependence and contagion in emerging equity markets', *Journal of Development Economics* **66**(2), 505–532.

Ehrmann, M., Ellison, M. and Valla, N. (2003), 'Regime-dependent impulse response functions in a markov-switching vector autoregression model', *Economics Letters* **78**(3), 295–299.

Enders, W. (2014), 'Applied econometric time series. 4th ed', *New York (US): University of Alabama* .

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation', *Econometrica: Journal of the econometric society* pp. 987–1007.

Engle, R. F. and Sarkar, D. (2006), 'Premiums-discounts and exchange traded funds', *The Journal of Derivatives* **13**(4), 27–45.

Fan, L. and Zhang, C. (2007), 'Beyond segmentation: The case of china's repo markets', *Journal of banking & finance* **31**(3), 939–954.

Fang, V. W., Huang, A. H. and Karpoff, J. M. (2016), 'Short selling and earnings management: A controlled experiment', *The Journal of Finance* **71**(3), 1251–1294.

Ferman, B. and Pinto, C. (2019), 'Synthetic controls with imperfect pre-treatment fit', *arXiv preprint arXiv:1911.08521* .

Figlewski, S. (1981), 'The informational effects of restrictions on short sales: Some empirical evidence', *Journal of Financial and Quantitative Analysis* pp. 463–476.

Figlewski, S. (1989), 'Options arbitrage in imperfect markets', *The journal of Finance* **44**(5), 1289–1311.

Firpo, S. and Possebom, V. (2018), 'Synthetic control method: Inference, sensitivity analysis and confidence sets', *Journal of Causal Inference* **6**(2).

Fong, K. Y., Holden, C. W. and Trzcinka, C. A. (2017), 'What are the best liquidity proxies for global research?', *Review of Finance* **21**(4), 1355–1401.

Fosback, N. G. (1976), *Stock market logic: a sophisticated approach to profits on Wall Street*, Inst for Econometric Research.

Freund, S., McCann, P. D. and Webb, G. P. (1994), 'A regression analysis of the effects of options introduction on stock variances', *The Journal of Derivatives* **1**(3), 25–38.

Füllbrunn, S. and Neugebauer, T. (2012), Margin trading bans in experimental asset markets, Technical report, Jena Economic Research Papers.

Gabor, D. (2016), 'The (impossible) repo trinity: the political economy of repo markets', *Review of international political economy* **23**(6), 967–1000.

Gallagher, D. R. and Segara, R. (2005), 'The performance and trading characteristics of exchange-traded funds', *Journal of Investment Strategy* **1**(1), 47–58.

García-Cicco, J. and Kawamura, E. (2014), 'Central bank liquidity management and" unconventional" monetary policies', *Economía* **15**(1), 39–87.

Garleanu, N. and Pedersen, L. H. (2007), 'Liquidity and risk management', *American Economic Review* **97**(2), 193–197.

Garleanu, N. and Pedersen, L. H. (2011), 'Margin-based asset pricing and deviations from the law of one price', *The Review of Financial Studies* **24**(6), 1980–2022.

Gastineau, G. L. (2004), 'The benchmark index etf performance problem', *The Journal of Portfolio Management* **30**(2), 96–103.

Gertler, M. and Kiyotaki, N. (2010), Financial intermediation and credit policy in business cycle analysis, *in* 'Handbook of monetary economics', Vol. 3, Elsevier, pp. 547–599.

Gobillon, L. and Magnac, T. (2016), 'Regional policy evaluation: Interactive fixed effects and synthetic controls', *Review of Economics and Statistics* **98**(3), 535–551.

Gorton, G. B., Metrick, A. and Ross, C. P. (2020), Who ran on repo?, *in* 'AEA Papers and Proceedings', Vol. 110, pp. 487–92.

Gorton, G. and Metrick, A. (2012), 'Securitized banking and the run on repo', *Journal of Financial economics* **104**(3), 425–451.

Goyal, A. and Saretto, A. (2009), 'Cross-section of option returns and volatility', *Journal of Financial Economics* **94**(2), 310–326.

Goyenko, R. Y., Holden, C. W. and Trzcinka, C. A. (2009), 'Do liquidity measures measure liquidity?', *Journal of financial Economics* **92**(2), 153–181.

Hall, P. (2013), *The bootstrap and Edgeworth expansion*, Springer Science & Business Media.

Hamilton, J. D. (1989), 'A new approach to the economic analysis of nonstationary time series and the business cycle', *Econometrica: Journal of the econometric society* pp. 357–384.

Hardouvelis, G. A. and Theodossiou, P. (2002), 'The asymmetric relation between initial margin requirements and stock market volatility across bull and bear markets', *The Review of Financial Studies* **15**(5), 1525–1559.

Harris, L., Namvar, E. and Phillips, B. (2014), *Price inflation and wealth transfer during the 2008 SEC short-sale ban*, SSRN.

Hartman, E. and Hidalgo, F. D. (2018), 'An equivalence approach to balance and placebo tests', *American Journal of Political Science* **62**(4), 1000–1013.

Hirano, K., Imbens, G. W. and Ridder, G. (2003), 'Efficient estimation of average treatment effects using the estimated propensity score', *Econometrica* **71**(4), 1161–1189.

Hsiao, C., Steve Ching, H. and Ki Wan, S. (2012), 'A panel data approach for program evaluation: measuring the benefits of political and economic integration of hong kong with mainland china', *Journal of Applied Econometrics* **27**(5), 705–740.

Hu, J., Wang, T., Hu, W. and Tong, J. (2020), 'The impact of trading restrictions and margin requirements on stock index futures', *Journal of Futures Markets* **40**(7), 1176–1191.

Hudgens, M. G. and Halloran, M. E. (2008), 'Toward causal inference with interference', *Journal of the American Statistical Association* **103**(482), 832–842.

Imai, K. and Kim, I. S. (2021), 'On the use of two-way fixed effects regression models for causal inference with panel data', *Political Analysis* **29**(3), 405–415.

Jares, T. E. and Lavin, A. M. (2004), 'Japan and hong kong exchange-traded funds (etfs): Discounts, returns, and trading strategies', *Journal of Financial Services Research* **25**(1), 57–69.

Johansen, S. et al. (1995), *Likelihood-based inference in cointegrated vector autoregressive models*, Oxford University Press on Demand.

Jones, C. M. and Lamont, O. A. (2002), 'Short-sale constraints and stock returns', *Journal of Financial Economics* **66**(2-3), 207–239.

Joyce, M., Miles, D., Scott, A. and Vayanos, D. (2012), 'Quantitative easing and unconventional monetary policy–an introduction', *The Economic Journal* **122**(564), F271–F288.

Kahn-Lang, A. and Lang, K. (2020), 'The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications', *Journal of Business & Economic Statistics* **38**(3), 613–620.

Kahraman, B. and Tookes, H. E. (2017), 'Trader leverage and liquidity', *The Journal of Finance* **72**(4), 1567–1610.

Kim, S. and Chen, H. (2019), 'From a quantity to an interest rate-based framework: Multiple monetary policy instruments and their effects in china', *Journal of Money, Credit and Banking* .

Kiyotaki, N. and Moore, J. (1997), 'Credit cycles', *Journal of political economy* **105**(2), 211–248.

Klee, E. and Stebunovs, V. (2011), 'A target treasury general collateral repo rate: is a target repo rate a viable alternative to the target federal funds rate?', *Board of Governors of the Federal Reserve System* **35**.

Koop, G., Pesaran, M. H. and Potter, S. M. (1996), 'Impulse response analysis in nonlinear multivariate models', *Journal of econometrics* **74**(1), 119–147.

Koren, Y. (2009), 'The bellkor solution to the netflix grand prize', *Netflix prize documentation* **81**(2009), 1–10.

Kreis, Y. and Licht, J. W. (2018), 'Trading on etf mispricings', *Managerial Finance* .

Krishnamurthy, A., Nagel, S. and Orlov, D. (2014), 'Sizing up repo', *The Journal of Finance* **69**(6), 2381–2417.

Krolzig, H.-M. (1998), 'Econometric modelling of markov-switching vector autoregressions using msvar for ox'.

Kumar, R., Sarin, A. and Shastri, K. (1995), 'The impact of index options on the underlying stocks: The evidence from the listing of nikkei stock average options', *Pacific-Basin Finance Journal* **3**(2-3), 303–317.

Levy, A. and Lieberman, O. (2013), 'Overreaction of country etfs to us market returns: Intraday vs. daily horizons and the role of synchronized trading', *Journal of Banking & Finance* **37**(5), 1412–1421.

Lin, C.-C., Chan, S.-J. and Hsu, H. (2006), 'Pricing efficiency of exchange traded funds in taiwan', *Journal of Asset Management* **7**(1), 60–68.

Liu, L., Wang, Y. and Xu, Y. (2020), 'A practical guide to counterfactual estimators for causal inference with time-series cross-sectional data', *Available at SSRN 3555463* .

Liu, S. (2010), 'Equity options and underlying stocks' behavior: Further evidence from japan', *International Review of Finance* **10**(3), 293–312.

Lucas, J. R. E., Lucas, R. E. and Gillman, M. (2012), *Collected papers on monetary theory*, Harvard University Press.

Luo, J., Ni, X. and Tian, G. G. (2020), 'Short selling and corporate tax avoidance: Insights from a financial constraint view', *Pacific-Basin Finance Journal* **61**, 101323.

Lütkepohl, H. (2005), *New introduction to multiple time series analysis*, Springer Science & Business Media.

Lv, D. and Ruan, Q. (2018), 'Asymmetric effect of margin-trading activities on price crashes: evidence from chinese stock market', *Applied Economics Letters* **25**(13), 900–904.

Lv, D. and Wu, W. (2019), 'Margin-trading volatility and stock price crash risk', *Pacific-Basin Finance Journal* **56**, 179–196.

Lv, D. and Wu, W. (2020), 'Margin trading and price efficiency: information content or price-adjustment speed?', *Accounting & Finance* **60**(3), 2889–2918.

Mancini, L., Ranaldo, A. and Wrampelmeyer, J. (2016), 'The euro interbank repo market', *The Review of Financial Studies* **29**(7), 1747–1779.

Mayhew, S. and Mihov, V. T. (2005), Short sale constraints, overvaluation, and the introduction of options, *in* 'AFA 2005 Philadelphia Meetings'.

Mayhew, S., Mihov, V. et al. (2000), 'Another look at option listing effects', *Institute for Quantitative Research in Finance* .

Meng, Q., Li, X., Chan, K. C. and Gao, S. (2020), 'Does short selling affect a firm's financial constraints?', *Journal of Corporate Finance* **60**, 101531.

Miller, E. M. (1977), 'Risk, uncertainty, and divergence of opinion', *The Journal of finance* **32**(4), 1151–1168.

Mizuta, T., Izumi, K., Yagi, I. and Yoshimura, S. (2015), 'Investigation of price variation limits, short selling regulation, and uptick rules and their optimal design by artificial market simulations', *Electronics and Communications in Japan* **98**(7), 13–21.

Ni, X. and Yin, S. (2020), 'The unintended real effects of short selling in an emerging market', *Journal of Corporate Finance* **64**, 101659.

Ni, X. and Zhu, W. (2016), 'Short-sales and stock price crash risk: Evidence from an emerging market', *Economics letters* **144**, 22–24.

Ogburn, E. L. and VanderWeele, T. J. (2017), ‘Vaccines, contagion, and social networks’, *The Annals of Applied Statistics* **11**(2), 919–948.

Pilar, C. and Rafael, S. (2002), ‘Does derivatives trading destabilize the underlying assets? evidence from the spanish stock market’, *Applied Economics Letters* **9**(2), 107–110.

Poterba, J. M. and Shoven, J. B. (2002), ‘Exchange-traded funds: A new investment option for taxable investors’, *American Economic Review* **92**(2), 422–427.

Qiao, Z. and Liu, Y. (2017), ‘Open market operation effectiveness in china’, *Emerging Markets Finance and Trade* **53**(8), 1706–1719.

Qiong, Y. D.-y. W. (2011), ‘Empirical research on the impact of margin trading on liquidity and volatility of shanghai security market [j]’, *Journal of Central University of Finance & Economics* **5**.

Robbani, M. G. and Bhuyan, R. (2005), ‘Introduction of futures and options on a stock index and their impact on the trading volume and volatility: Empirical evidence from the djia components’, *Derivatives Use, Trading & Regulation* **11**(3), 246–260.

Rothman, P. (1998), ‘Forecasting asymmetric unemployment rates’, *Review of Economics and Statistics* **80**(1), 164–168.

Rubin, D. B. (1980), ‘Randomization analysis of experimental data: The fisher randomization test comment’, *Journal of the American statistical association* **75**(371), 591–593.

Sato, T. and Matsuda, Y. (2017), ‘Spatial autoregressive conditional heteroskedasticity models’, *Journal of the Japan Statistical Society* **47**(2), 221–236.

Sato, T. and Matsuda, Y. (2021), ‘Spatial extension of generalized autoregressive conditional heteroskedasticity models’, *Spatial Economic Analysis* **16**(2), 148–160.

Scheinkman, J., Xiong, W. et al. (2003), ‘Overconfidence, short-sale constraints, and bubbles’, *Journal of Political Economy* **111**(6), 1183–1219.

Semmler, W. and Zhang, W. (2007), ‘Asset price volatility and monetary policy rules: a dynamic model and empirical evidence’, *Economic Modelling* **24**(3), 411–430.

Sharif, S., Anderson, H. D. and Marshall, B. R. (2014), 'Against the tide: The commencement of short selling and margin trading in mainland china', *Accounting & Finance* **54**(4), 1319–1355.

Sheehan, K. (2012), The 2008 emergency regulation of short selling in the united kingdom, united states, and australia, *in* 'Handbook of Short Selling', Elsevier, pp. 169–179.

Shi, L. and Xiao, Y. (2020), 'Dynamic asset pricing with interactions between short-sale and borrowing constraints', *Review of Asset Pricing Studies* .

Sims, C. A. (1980), 'Macroeconomics and reality', *Econometrica: journal of the Econometric Society* pp. 1–48.

Skinner, D. J. (1989), 'Options markets and stock return volatility', *Journal of Financial economics* **23**(1), 61–78.

Sobel, M. E. (2006), 'What do randomized studies of housing mobility demonstrate? causal inference in the face of interference', *Journal of the American Statistical Association* **101**(476), 1398–1407.

Stock, J. H. and Watson, M. W. (2002), 'Forecasting using principal components from a large number of predictors', *Journal of the American statistical association* **97**(460), 1167–1179.

Sui, C., Lung, P. and Yang, M. (2021), 'Index option trading and equity volatility: Evidence from the sse 50 and csi 500 stocks', *International Review of Economics & Finance* **73**, 60–75.

Sun, R. (2013), 'Does monetary policy matter in china? a narrative approach', *China Economic Review* **26**, 56–74.

Svensson, L. E. (1986), 'Sticky goods prices, flexible asset prices, monopolistic competition, and monetary policy', *The Review of Economic Studies* **53**(3), 385–405.

Tibshirani, R. J. and Efron, B. (1993), 'An introduction to the bootstrap', *Monographs on statistics and applied probability* **57**, 1–436.

Tong, H. (1983), *Threshold models in non-linear time series analysis*, Springer Lecture Notes in Statistics, New York.

Tuchschmid, N. S., Wallerstein, E. and Zaker, S. (2012), Short selling in an asset allocation framework—the search for alpha, *in* 'Handbook of Short Selling', Elsevier, pp. 453–465.

VanderWeele, T. J., Ogburn, E. L. and Tchetgen, E. J. T. (2012), 'Why and when" flawed" social network analyses still yield valid tests of no contagion', *Statistics, Politics, and Policy* **3**(1).

Wang, Y.-C., Tsai, J.-J. and Chen, K.-W. (2019), Monetary policy transmission: The linkages between repurchase operations and market interest rates, *in* '2019 International Conference on Contemporary Education and Society Development (ICCESD 2019)', Atlantis Press, pp. 176–180.

Wang, Y.-C., Tsai, J.-J. and Lu, L. (2019), 'The impact of chinese monetary policy on co-movements between money and capital markets', *Applied Economics* **51**(45), 4939–4955.

Woodford, M. and Walsh, C. E. (2005), 'Interest and prices: Foundations of a theory of monetary policy', *Macroeconomic Dynamics* **9**(3), 462–468.

Xiangyou, L. (2014), 'An empirical study on the impact of margin trading on the etfs market quality based on the difference in difference model', *Review of Investment Studies* **33**(6), 138–148.

Xie, S. and Jia, Y. (2019), 'Margin trading and volatility: Further evidence from china's stock market', *Emerging Markets Finance and Trade* **55**(6), 1375–1387.

Xiong, X., Gao, Y. and Feng, X. (2017), 'Successive short-selling ban lifts and gradual price efficiency: evidence from china', *Accounting & Finance* **57**(5), 1557–1604.

Xu, Y. (2017), 'Generalized synthetic control method: Causal inference with interactive fixed effects models', *Political Analysis* **25**(1), 57–76.

Ye, Q., Zhou, S. and Zhang, J. (2020), 'Short-selling, margin-trading, and stock liquidity: Evidence from the chinese stock markets', *International Review of Financial Analysis* **71**, 101549.

Zeng, F., Huang, W.-C. and Hueng, J. (2016), 'On chinese government's stock market rescue efforts in 2015', *Modern Economy* **7**(4), 411–418.

Zhou, X. and Li, H. (2019), 'Buying on margin and short selling in an artificial double auction market', *Computational Economics* **54**(4), 1473–1489.