Essays on the Application of Derivatives: Evidence from the United States

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Abstract

My thesis focuses on examining the application of financial derivatives on U.S. market. In Chapter 1, I test whether the introduction of derivatives affects their underlying assets. By examining the flow of money to volatility-related exchange-traded products, I find evidence that the trading of those derivatives affects the underlying assets, but that the impacts are not stronger during market downturns. In Chapter 2, I analyze the determinants of expected market volatility proxied by the VIX index. I document that the relationship between expected market volatility and its determinants is subject to changes over time. In Chapter 3, I investigate whether regulations in the post-GFC period changed banks' attitudes towards and use of derivative products. The analysis of the introduction of the Dodd-Frank Act reveals that banks were exposed to lower systemic risk associated with derivatives usage but to higher overall risks after the commencement of the act.

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Table of CONTENTS

List of Figures

List of Tables

PART I

INTRODUCTION

A considerable portion of financial innovations over recent decades has come from the emergence of derivatives markets. Derivatives are financial instruments whose value is derived from the value of underlying assets, such as equities, bonds, exchange rates, commodities, residential mortgages, commercial mortgages and even other derivatives. The most common forms of derivative products are options, forwards, futures and swaps. The first recorded example of a derivatives transaction dates back to around 600 BC, when the philosopher Thales of Miletus positioned himself to profit from the rising price of oil by negotiating what were effectively call options on olive oil.

Financial derivatives can be used by investors as tools for hedging or speculation purposes. Derivatives for hedging are used to manage risks by providing offsetting compensation in case of an undesired event. More specifically, one party in a derivatives contract could transfer the risks related to the price of the underlying assets to its counterparty. By using financial derivatives, corporations are able to mitigate potential financial distress cost (e.g. Smith and Stulz, 1985; Norden, Silva Buston, and Wagner, 2014; Bartram, 2017) and avoid underinvestment issues (e.g. Froot, Scharfstein, and Stein, 1993; Deng, Elyasiani, and Mao, 2017), thereby increasing firm value. On the other hand, derivatives can be used for speculation purposes and acquiring risks. Investors can use derivatives to speculate on the value of the underlying assets, betting that the future value of the underlying assets will move in the expected direction without having prior positions in those assets. Such speculations expose those investors to higher risks (e.g. Choi and Elyasiani, 1997; Minton, Stulz and Willamson, 2005; Li and Marinč, 2014).

Another important benefit of derivatives is improved market efficiency through arbitrage trading. Investors can get positions in different derivatives on the same underlying asset or derivatives markets, seeking chances to lock in a riskless profit by offsetting these positions. Such arbitrage trading activities will rapidly adjust the price, eradicate the arbitrage opportunities and therefore improve market efficiency (e.g. Partnoy, 1996; Figlewski, 2017). Derivatives also enable individuals to get exposure to hard-to-trade assets more efficiently. For instance, investors can track the performance of the equity market conveniently with stock index futures, rather than including all individual stocks listed in the index in their investment portfolio, which is laborious and difficult to manage.

However, despite their benefits, derivatives have been labeled by Warren Buffet as "financial weapons of mass destruction", and, particularly over-the-counter (OTC) derivatives, are criticized for causing debacles and financial crises (e.g. Bedendo and Bruno, 2012; Donaldson and Micheler, 2018).

OTC derivatives are privately negotiated and traded directly between two parties instead of through an exchange or other intermediary. Derivatives contracts, such as swaps, forwards and exotic options are normally traded over the counter. The OTC derivatives market is the biggest market for derivatives trading and is largely unregulated, since the information disclosure between the involved parties is quite low. The main participants in the OTC derivatives market are banks and other highly sophisticated parties (e.g. hedge funds). A vast amount of criticism has been made about the role of banks' use of OTC derivatives in fueling the 2007-2009 global financial crisis.

Unlike OTC derivatives, exchange-traded derivatives are traded on specialized markets, namely the exchanges. These derivative contracts are defined and standardized by the exchange and allow market participants to trade. The derivatives exchanges act as intermediaries to all transactions of exchange-traded derivatives and provide guarantees by taking margins from both parties involved in the derivatives contract.

My thesis consists of three essays on derivatives markets and investigates both exchange-traded derivatives and OTC derivatives. The first essay contributes to the literature by examining to what extent the introduction of derivatives products affects the underlying assets. More specifically, I answer the question of the extent to which the extensive flow of money to the volatility-related exchange-traded products affects the level of the underlying VIX index.[1]

The second essay in my work provides empirical evidence on the determinants of investors' fear gauge – the VIX index. In particular, I empirically test the implication of the theoretical model posed by Pastor and Veronesi (2013) and the theoretical model formulated by Dumas, Kurshev, and Uppal (2009). In this essay, I also examine the role of representativeness bias in determining the level of the VIX.

Finally, the third essay contributes to the debate on whether and to what extent regulations in the post-financial-crisis period change banks' attitudes towards financial derivatives.[2] In particular, I answer the question of whether the Dodd-Frank Act, as a response to the financial crisis, has met its objectives of restricting the effects of derivatives on banks' systemic risk.

The rest of the thesis is organized as follows. Part II contains the three essays.

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1 Previous studies have examined how the introduction of derivatives, such as futures and options, affects the volatility of the underlying assets (e.g. Bollen, 1998; Bologna and Cavallo, 2002; Shenbagaraman, 2003; Spyrou, 2005; Drimbetas, Sariannidis and Porfiris, 2007; Kasman and Kasman, 2008) and document mixed findings.

2 According to Fidrmuc (2013), differences in regulation could have influence on banks' activities, such as lending.

Chapter 1 examines the impacts of derivatives on the underlying asset. Chapter 2 analyzes the determinants of expected market volatility. Chapter 3 investigates the effects of regulations on banks' attitude towards derivatives in the post-crisis period. Part III concludes.

PART II

ESSAYS

Chapter 1

Does the tail wag the dog? Evidence from fund flow to VIX ETFs and ETNs

Abstract

This study investigates if and how the fund flows to VIX exchange-traded funds (ETFs) and VIX exchange-traded notes (ETNs) impact the underlying volatility VIX index. The VIX ETFs and ETNs are divided into four groups depending on their investment strategy. I found that each group has a very distinctive fund flow pattern, reflecting the mean-reverting character of the VIX. I found that generally higher fund flows to VIX exchange-traded funds and notes which apply a normal tracking strategy tend to increase the value of the VIX, while higher fund flows to VIX exchange-traded funds and notes which apply an inverse tracking strategy decrease the value of the VIX. Moreover, I show that money flows to VIX exchange-traded products is insufficient to contribute to market instability during market downturns. The results of this study provide arguments for the discussion on the impact of exchange trade products on their underlying products (see SEC's File No. S7-11-15).

Keywords: VIX,Exchange-traded fund, Exchange-traded note, Fund flow, VIX future price, VIX future price term structure

JEL codes: G11, G12

1.1 Introduction

After the recent global financial crisis, including variance-related instruments in investment portfolios has been emphasized by many academic researches (Chen, Chung and Ho, 2010; Santon, 2011; Whaley, 2013; DeLisle, Doran and Krieger, 2014). Market participants prefer to include volatility products in their portfolios to enjoy diversification benefits during periods of turmoil. Among those variance-related products, the instruments whose performance is linked to the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) level have become most popular. The VIX is a measure of the implied volatility of S&P 500 index options. As a market volatility index, the VIX represents the market's expectation of stock market volatility over the next 30-day period. In recent years, it has become a commonly accepted "fear gauge" for many investors.

The VIX is not an index in which market participants are allowed to directly invest since its inception in 1993. However, volatility trading then was not restricted to direct investment in the VIX index, as there were a few available approaches on the market, such as combinations of static positions in the market index options with dynamic trading in the underlying or straddle, strangle combinations[3] (Neuberger, 1990; Dupire, 1997; Carr and Madan, 1998). Considering the option positions need to be monitored and rebalanced frequently, those approaches of trading in volatility required a high level of engagement from investors. On top of that, volatility trading with market index options portfolios was much more complicated than any buy-and-hold strategy commonly used

[3]Long positions in a straddle and a strangle could benefit from a rise in volatility; while delta-hedging an option position provides exposure to the difference between the realized volatility and the anticipated volatility used in pricing and hedging the option.

in the case of exchange-traded fund (ETF) and exchange-traded note (ETN) investments.

The CBOE Futures Exchange (CFE) responded to the growing demand for simplified volatility trading. On March 26, 2004, the first-ever trading in futures contract on the VIX started on the CFE, providing investors a straight approach to trade in expected market volatility. On February 24, 2006, VIX option contracts became another type of VIX-related products available to trade, providing investors more flexibility in volatility investing. VIX options and futures shortly became actively traded contracts on the CFE. The average daily trading volume of VIX options contracts has grown considerably from 0.13 million contracts in 2009 to 0.57 million contracts in 2015, which then takes up more than half of the total daily trading volume of all S&P 500 index option groups[4] (0.97 million contracts)[5]. The average trading volume in VIX futures climbed from 4.5 thousand contracts in 2009 to 205 thousand contracts in 2015[6], dwarfing nearly all other futures trading on the CFE.

Compared to those trading approaches with market index options, VIX futures and options contracts are more direct instruments to trade volatility for market participants. However, VIX futures and options contracts are still complex investments particularly for individual investors, in spite of their popularity. While sophisticated investors can trade VIX futures and options for multiple purposes such as speculation, directional exposure, arbitrage, diversification and hedging, it is not so easy and cost-efficient for unsophisticated investors to trade them to get exposure to market volatility. The need to provide volatility-related exchange-traded products to a wide variety of investors has

[4] The S&P 500 option groups include SPX Options Traditional, SPX Options Non-Traditional, SPX Options - Mini and SPY Options, covering seven types of SPX options.

[5] The data were retrieved from CBOE Historical Options Data: http://www.cboe.com/data/putcallratio.aspx.

[6] The data were retrieved from the website http://cfe.cboe.com/data/historicaldata.aspx.

been increasingly emphasized. Commenting on the issuance of VIX exchange-traded products, Coleman (2012) states that "Barring some unforeseen complication, individual investors and their professional advisors should soon be able to do much the same in a seemingly less complicated and affordable manner."

Indeed, in February 2009, Barclays iPath launched the S&P 500 VIX Short-Term Futures Exchange-Traded Notes (NYSE: VXX) and S&P 500 VIX Mid-Term Futures Exchange-Traded Notes (NYSE: VXZ), representing the emergence of VIX futures-based exchange-traded products. Those exchange-traded products invest in VIX futures indexes, thereby providing investors with exposure to market volatility. For instance, the VXX ETN tracks the S&P VIX Short Term Futures Index Total Return. The index itself is designed to follow the changes in the value of short-term VIX futures contracts. According to its prospectus, the VXX ETN is designed to provide investors with exposure to one or more maturities of futures contracts on the VIX index. These VIX ETNs quickly became the most popular variance-related instruments among investors because of their low costs, tax efficiency and stock-like features. In 2010, just one year after their issuance, the average daily trading volume of the VXX ETNs reached around 19 million shares and they have been growing fast. Following the successful introduction of the VXX and VXZ, more and more VIX-related ETNs and ETFs have been launched. These instruments track different VIX futures indices and other VIX-related indices, and thereby provide investors with a wider variety of investment choices. Currently, there are more than 20 VIX-related exchange-traded products, making it more convenient for global investors to get exposure to market volatility in a cost-efficient manner. For the sake of simplicity, I refer to VIX ETNs and ETFs as VIX exchange-traded products (ETPs).

The fast growing of investors' interest in volatility-linked products has been accompanied by an increase in academic output on related topics. Existing literature on the VIX index and VIX-related products has evolved into several main streams including the pricing and modeling of the VIX index and VIX derivatives; the interaction between the VIX and VIX-related products; and the performance of VIX ETPs. So far, few attempts have been made to examine the flows to VIX ETPs and the possible impact of the fund flows on the VIX index. The literature, however, has documented that fund flow matters to other investment vehicles, such as mutual funds (Edelen and Warner, 2001; Boyer and Zheng, 2009; Ben-Rephael, Kandel and Wohl, 2011; Christoffersen, Musto, and Wermers, 2014) and hedge funds (Brown, Goetzmann, Liang and Schwarz, 2008; Boyson, Stahel and Stulz, 2010; Dichev and Yu, 2011; Li, Zhang and Zhao, 2011; Horst and Salganik, 2014). The impacts of fund flow have also been examined in the context of ETFs. Kalaycıoğlu (2004) investigates the flow-return relationship in ETFs at individual and aggregate levels and finds significant negative correlation between ETF flows and market returns. Staer (2014) explores the relation between daily contemporaneous ETF flows and their underlying securities' returns and reports a positive, which is also supported by Chang and Ke (2014). Clifford, Fulkerson and Jordan (2014) investigate the drivers of equity ETF flows and find that higher volume, smaller spreads and higher price to net asset value ratios increase ETF flows.

Taking into account the previously reported relationships between fund flow and performance, one may expect that the money flow to VIX ETPs can impact the performance of the underlying VIX index. In the aftermath of the collapse of VelocityShares Daily 2x VIX Short-Term ETN (TVIX),[7] the Security and Exchange

[7]On February 21, 2012, Credit Suisse stopped issuing new shares in VelocityShares Daily 2x VIX Short Term ETN (TVIX) due to internal limits on the size of ETNs; as a result, the share price of the ETN increased to $14.43, 89% higher than its $7.62 net asset in one month. Next it immediately plunged 29%

Commission (SEC) decided to look into the trading of it, and the financial media started to ask questions about whether the extensive money flows to ETFs and ETNs may have an impact on the underlying itself.

An article published in the *Financial Times* raises concerns that distorted messages about future expectations of market behavior may be sent by the VIX futures markets due to the popularity of ETPs.[8] At the same time, the *Wall Street Journal* asked to what degree the money flow into VIX products more broadly affects the VIX itself.[9] These concerns are shared by Alexander and Korovilas (2012) and Asensio (2013), who suggest that as VIX futures have become more accessible to general investors, the inflows can create distortions in VIX futures markets, especially for short-dated tenors, which are most actively used for the management of VIX ETPs.

On June 12, 2015, SEC filed an official document No. S7-11-15, to seek public comment on topics related to the listing and trading of exchange-traded products on national securities exchanges and sales of these products by broker-dealers. In that file, comments were requested on the nature, extent, and potential causes of premiums and discounts across the wide range of ETP strategies and holdings. Furthermore, the Item 17 in the file precisely raise the question: "To what extent, if any, does trading activity in ETP Securities affect price discovery, price correlation, liquidity, or volatility in the ETP's underlying or reference assets?" which confirms the concerns between ETPs and the underlying index.[10]

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after Credit Suisse reopened issuance and then dropped another 30% on the next day (see Russolillo, 2012; Lauricella, Eagkesham and Dieterich, 2012; Dieterich and Kiernan, 2012).

[8]Makan and Kaminska (2012), "ETF rush muddies the waters on volatility," Financial Times. http://www.ft.com/cms/s/0/2c50013a-78f6-11e1-88c5-00144feab49a.html#axzz3cqbDRjSP

[9] Lauricella (2012), "Are TVIX, Other ETNs Wagging the Tail of the VIX Dog?" Source: http://blogs.wsj.com/marketbeat/2012/03/29/are-tvix-other-etns-wagging-the-tail-of-the-vix-dog

[10] The CME Group released a statement that stock index futures market are more liquid than ETP markets,

This study focuses on the examination of the fund flows to VIX ETPs and their effect on the VIX index. In addition, the study answers Question 17 in SEC's File No. S7-11-15, on how the ETP can affect the underlying using results obtained for VIX ETPs market. The contribution of the study is twofold. Firstly, reported results help to understand the dynamics of fund flow to different VIX ETP groups as a function of market performance. Secondly, the findings show that while the aggregated flow has marginal effects on the VIX index, the fund flow to a few specific groups of those VIX ETFs and ETNs have significant impacts on the VIX index. Moreover, I show that there is no extra impact of the flow on the VIX during a bear market, suggesting that the trading in VIX ETPs during a bearish period do not destabilize the underlying market.

The remainder of this chapter is organized as follows. Section 1.2 discusses technical details concerning VIX, VIX futures and VIX ETPs. Section 1.3 reviews the related literature and Section 1.4 outlines the hypotheses. Section 1.5 presents the data and methodology. Section 1.6 presents the results of the empirical analysis on the fund flow to VIX ETPs. Section 1.7 summarises the findings and concludes.

1.2 VIX, VIX futures and VIX ETPs

1.2.1 VIX Index

As discussed, the VIX is a trademarked ticker symbol for the CBOE Market volatility index and represents one measure of the market's expectation of stock market

and therefore stock index futures market functions as the leading price indicator. On the other hand, BlackRock commented that more ETFs are becoming the true market and the underlying assets may eventually catch up with any gap between the two. Though it is not agreed precisely on which product is leading prices, the statements show the nature of derivative products has changed and they could pose risks to the underlying securities.

volatility over the next 30-day period. The VIX gets more attention from investors due to the fact that the movement of the index provides an indication of the trend of the stock market. When there are concerns among investors about a potential decline in the equity market, hedgers buy more S&P 500 index option puts as insurance for their portfolio against the unfavored market move. As a consequence, more investors demand increases the price of index options and lead to a higher VIX level (Whaley, 2008). In other words, the VIX is an indicator that reflects the price of portfolio insurance. As the VIX is found typically to trend downwards in a bull market and upwards in a bear market, investors could influence their investment decisions and actions based on the level of the VIX index (Fleming, Ostdiek and Whaley, 1995; Whaley, 2008). In addition, the VIX has been frequently applied as a proxy for realized market volatility in recent research, and has been proved that it outperforms other risk measurements of spot volatility (e.g. Christiansen, Ranaldo and Soderlind, 2011; Kanniainen, Lin and Yang, 2014).

The VIX was introduced by CBOE in 1993 and was originally designed to measure the market's expectation of 30-day volatility implied by the price of at-the-money S&P 100 Index (OEX Index) option, the most actively-traded index options in the U.S. then. Since its inception, the VIX soon became the most popular benchmark for U.S. stock market volatility and has been regularly featured in leading financial news and publications (e.g. the Wall Street Journal, Barron's, Bloomberg). As the S&P 500 Index option market gradually became the core index option market, later in 2003, the VIX was updated by CBOE together with Goldman Sachs, to measure the expected volatility within a new way, which is based on the S&P 500 Index. Different from the old VIX which only estimated the implied volatility of at-the-money S&P 100 index option, the new way estimates expected market volatility by combining the weighted prices of S&P 500 Index call and put options (European-style exercise) over a wide range of strike prices.

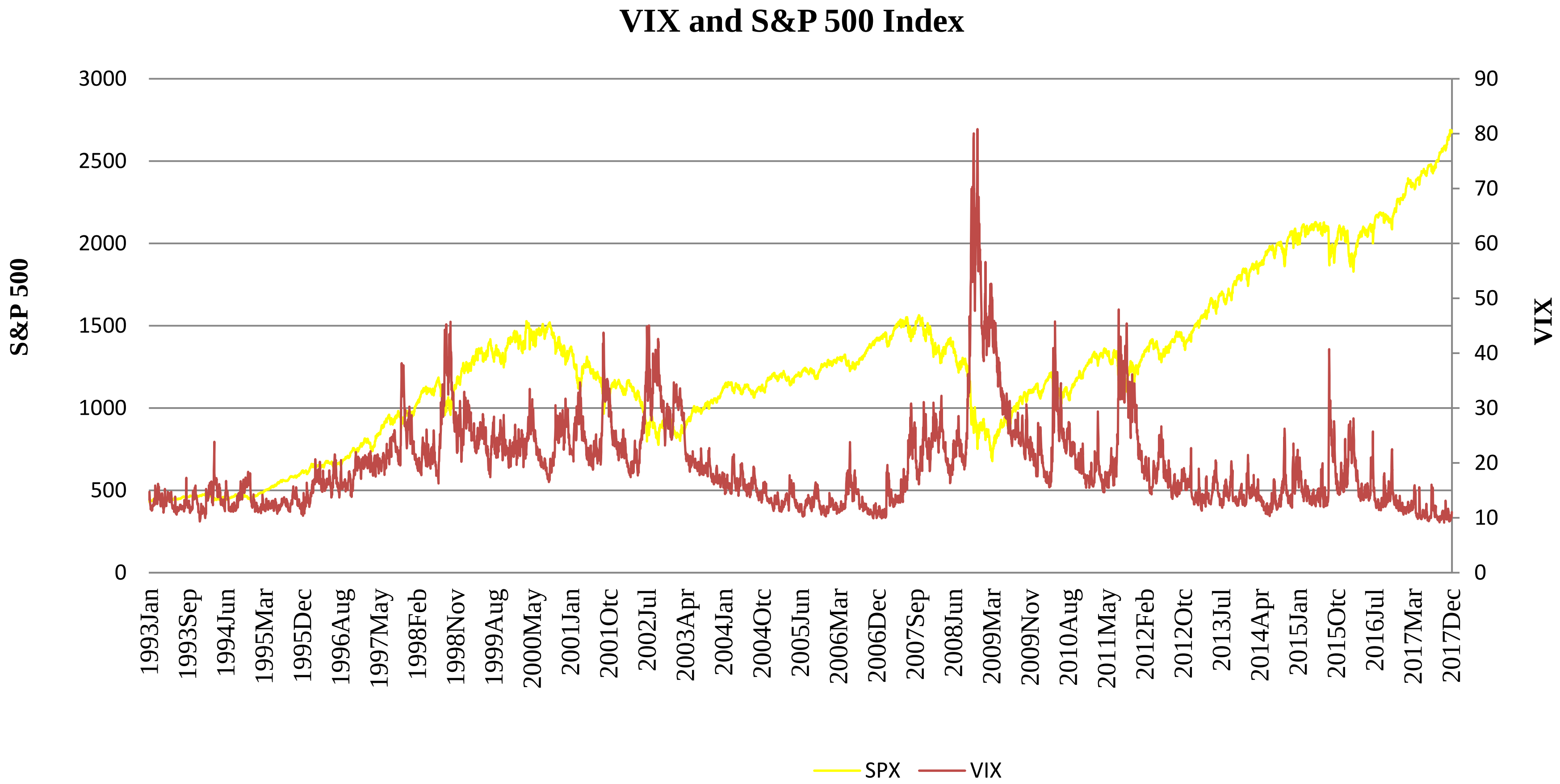
1.2.1.1 Mean-reversion and history of VIX index

The key property of the VIX is that it is a mean-reverting time series (Whaley, 2008). More specifically, when the VIX is quite high (low), it tends to get pulled back down (up) to its long-run mean. Another important property of the VIX is its asymmetric relationship with the equity market index. When expected market volatility spikes, market participants demand a higher risk premium and consequently the prices of stocks decline, and, when expected market volatility decreases, investors demand a lower risk premium, so the prices of stocks rise. This suggests the relation between the percentage change in the VIX should be proportional to the percentage return of the S&P 500 index. However, empirical evidence has been found that the absolute rate of change in the VIX is higher when the equity market falls than when it rises (Whaley, 2008). This asymmetry could be attributed to investors' demand for S&P 500 Index put options as portfolio insurance when the market is in turmoil.

In order to gauge the behavior of the VIX, I present the time-series value of the VIX and S&P 500 index in Figure 1.1. The time window starts from 1993, the year when the VIX was officially introduced, through December 2017. There are several noteworthy observations. It can be found in the figure that there are periods when the VIX reaches quite high levels. More specifically, the VIX spiked in October 1997 following a stock market sell-off when the Dow fell 555 points. The October 1998 spike occurred in a period of general nervousness in the stock market. The recession periods of the early 2000s is also associated with the a VIX level. The peak level of the VIX is observed during the recent 2007-2009 crisis, when the value of the VIX closed at 80.86 on November 20, 2008. The VIX jumps in May 2010 followed the concerns about European debt and the spike in August 2010 is accompanied by the fears about a slowing global economic recovery as well as S&P's downgrade on the U.S. In the aftermath of each spike, the VIX returned to more normal levels, which is consistent with the mean-reversion of the fear gauge.

In addition, it can be noticed in Figure 1.1 that although the closing levels of the VIX and the S&P 500 index appear to move in opposite directions during most of the time, there are periods when stock prices and the VIX run up at the same time. For example, in January 1999, the rising VIX was accompanied by an increasing level of the S&P 500 index. Such patterns can also be found in the first two months of 1995, June and July of 1997, and December 1999, which might suggest investors' fears could spike even during market advances.

Figure 1.1


VIX and S&P 500 Index
S&P 500
VIX
3000
2500
2000
1500
1000
500
0
90
80
70
60
50
40
30
20
10
0
1993Jan
1993Sep
1994Jun
1995Mar
1995Dec
1996Aug
1997May
1998Feb
1998Nov
1999Aug
2000May
2001Jan
2001Otc
2002Jul
2003Apr
2004Jan
2004Otc
2005Jun
2006Mar
2006Dec
2007Sep
2008Jun
2009Mar
2009Nov
2010Aug
2011May
2012Feb
2012Otc
2013Jul
2014Apr
2015Jan
2015Otc
2016Jul
2017Mar
2017Dec
SPX
VIX

1.2.2 VIX futures

Since the VIX index does not allow market participants to invest directly in it, the main available approaches of volatility trading were restricted to the combinations of dynamic and complicated positions in options until 2004. These approaches were quite costly to even sophisticated investors as they needed to monitor the complicated option positions and rebalance frequently. As the market demand grew dramatically for simplified and straight forward volatility trading, the CBOE Futures Exchange (CFE) introduced VIX futures contracts on March 26, 2004, making it possible for market participants to directly trade volatility.

The prices of VIX futures could be either higher or lower than the current value of the underlying VIX index. The reason behind is that market participants' expectation on the volatility may vary from month to month. For instance, if the VIX index is 20 in August, the market expectation for the VIX could be higher than 20 in October and lower than 20 in December. As a consequence, the October VIX futures will be trading at a price above 20 while the December VIX futures will be trading below 20.

The pricing relationship between VIX futures and the underlying VIX index is different from that of other future contracts. In particular, VIX futures price is not given by a cost-of-carry model (Grunbichler and Longstaff, 1996), by which common futures contracts replicate the performance of the underling instrument. The cost-of-carry model suggests that, for an investor able to replicate the performance of the underlying instruments, there could be arbitrage opportunity where the investor can take advantage of the "mispricing" between a futures contract and the underlying asset. These arbitrage trading activities lead to a relatively narrow range for the trade of futures contracts, and therefore the price of futures contract is close to the price of the underlying instrument.

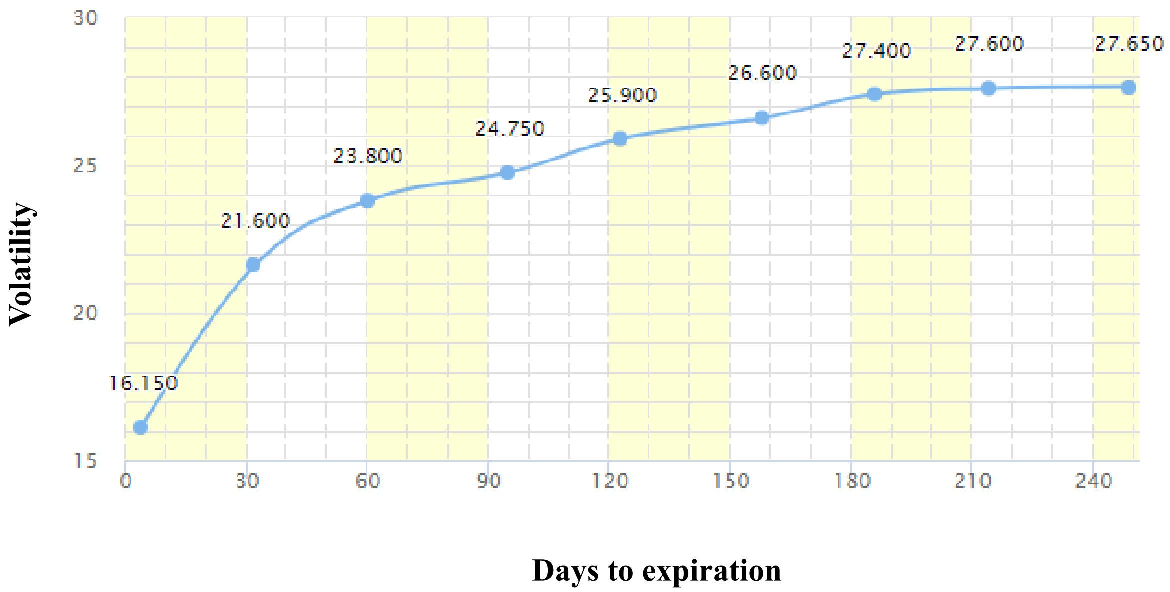
In contrast to the arbitrage trading discussed above, there is no arbitrage value relationship between VIX futures contract and the underlying VIX index. The VIX index is calculated using the mid-point between the bid and ask prices of the S&P 500 index option contracts. This mid-point pricing does not necessarily represent a real market trading price of a VIX futures contract. Consequently, market investors are unable to quickly trade S&P 500 option contracts to lock in the 30-day implied volatility versus the value of the VIX index.

The term structure of VIX futures (implied volatility) is the curve of VIX futures prices for periods extending from the current date to different future dates up to nine near-term serial months. Points of the curve at different terms present the expected market volatility for the corresponding future dates, and could be estimated from S&P 500 Index option prices with matching expirations. The VIX futures term structure could typically be either upward or downward sloping, which is referred as the market condition of "contango" or "backwardation". "Contango" indicates a market condition in which the price of a VIX futures contract closer to expiration is lower. In a contango market, the price of VIX futures contract increases with the time to expiration, and the curve of VIX futures term structures presents an upward slope. Figure 1.2 presents the VIX futures term structure on March 16, 2012, when the contango of VIX futures term structure reached the highest level after recent global financial crisis.[11]

[11] Source: VIX Central. Accordingly, the level in contango (backwardation) is calculated as the ratio of price difference between second-front month and first-front month VIX futures and then minus one.

Figure 1.2

VIX futures term structure on March 16, 2012 (Contango)

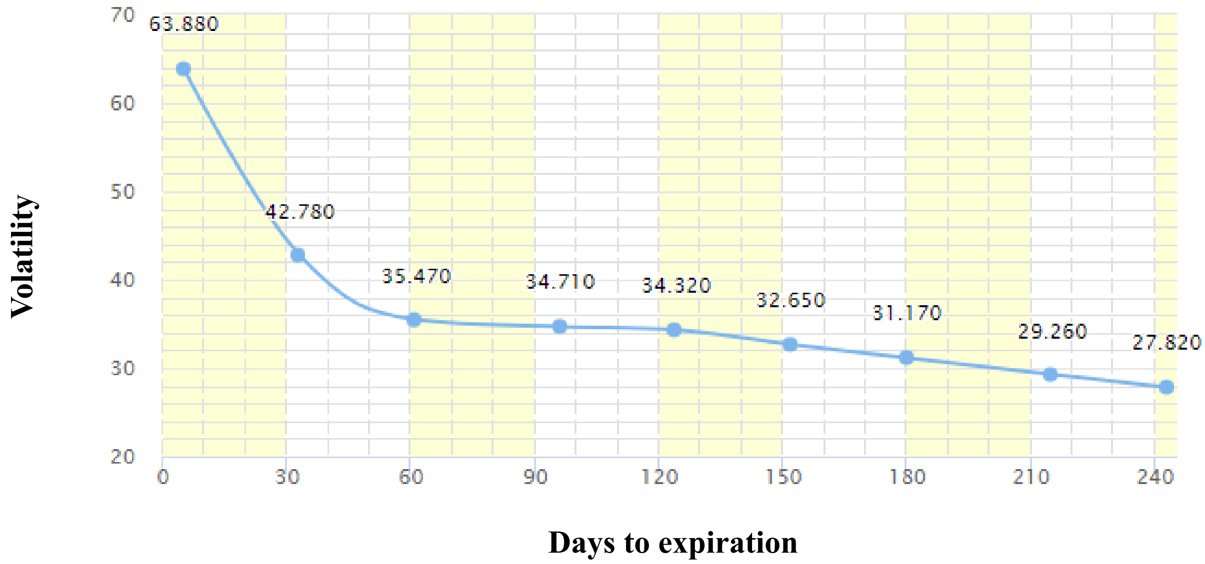


In most of time, VIX futures term structure is observed in contango, which suggests that the market expected volatility over longer periods is higher than short periods.

On the other hand, backwardation refers a market condition in which the price of futures contract declines as the VIX futures contract gets further to expiration. In a backwardation market, the price of a VIX futures contract decreases as the time to expiration gets longer, and the curve of VIX futures term structures presents a downward slope. Periods of backwardation are not that common as contango and typically accompanied by volatile periods.

Figure 1.3

VIX futures term structure on Oct 16, 2008 (Backwardation)



A steep backwardation of VIX futures term structure suggests that market investors believe that the current market volatility is too high and expect it would decline in the future. Figure 1.3 presents VIX futures term structure on October 16, 2008, when the backwardation in VIX futures term structure reached its highest level during the GFC.

1.2.2.2 VIX futures indices

In order to provide market participants straight outcome of holding long and/or short positions in VIX futures contracts, the S&P has generated more indices comprised of different VIX futures contracts since 2009. There are more than ten indices in the S&P VIX Futures Index Series, namely the S&P 500 VIX Short-Term Futures Index, S&P 500 VIX Mid-Term Futures Index, S&P 500 VIX 2M Futures Index, S&P 500 VIX 3M Futures Index, S&P 500 VIX 4M Futures Index, S&P 500 VIX 6M Futures Index, S&P 500 VIX Futures Term-Structure Index, S&P 500 VIX Short Term Futures Daily Inverse

Index, S&P 500 VIX Mid Term Futures Daily Inverse Index, and S&P 500 VIX Front Month Futures Index, each of which consists of only VIX futures contracts.

Among the S&P VIX Futures Index Series, the most popular two tracked by VIX exchange-traded products are the S&P 500 VIX Short-Term Futures Index and S&P 500 VIX Mid-Term Futures Index. The S&P 500 VIX Short-Term Futures Index was launched on Jan 22, 2009. The index provides investors the outcome of a combined long position in the next two near-term VIX futures contracts. More specifically, the S&P 500 VIX Short-Term Futures Index replicates a position that rolls the nearest month VIX futures to the next month on a daily basis in equal fractional amounts, and therefore measures the return of a constant one-month rolling long position in the first and second month VIX futures contracts.

At the start of the roll period, all the weight of S&P 500 VIX Short-Term Futures Index is allocated to the first (shorter-term) VIX futures contract. Then on each subsequent business day, a fraction of the first month VIX futures holding is sold with an equal notional amount of the second month (longer-term) VIX futures bought. The fraction is proportional to the number of first month VIX futures contracts as of the previous index roll day, and inversely proportional to the number of days in the current roll period. In this approach, the initial position in the first month VIX futures contract is progressively rolled to the second month contract, until the beginning of next roll period. Then the old second month VIX futures contract becomes the new first month contract and is sold on each subsequent business day afterwards as the process starts again.[12]

The S&P 500 VIX Mid-Term Futures Index was also introduced on Jan 22, 2009.

[12] According to S&P, the weight of each component in the VIX futures index is also adjusted every day to ensure that the change in total dollar exposure for the index is only due to the price change of each contract and not due to using a different weight for a contract trading at a higher price.

The index utilizes the prices of the fourth, fifth, sixth and seventh month VIX futures contracts and measures the return of a constant three-month rolling long position in those futures.

Similarly, at the start of the roll period, an equal weight is allocated to the fourth, fifth and sixth month VIX futures contracts. The initial position in the fourth month contract is progressively moved to the seventh month contract over the course of the month, until the following roll period begins when the old fifth month VIX futures contract becomes the new fourth month VIX futures contract and gets sold every day afterwards as the process begins again.

1.2.3 VIX ETF and ETN

Launched in 2009, VIX exchange-traded products have become one of the most actively traded categories of ETPs. Similar to stocks, VIX ETPs make volatility trading more convenient for market participants by providing exposures to relevant VIX futures indices. There are two types of VIX ETPs, namely VIX ETF and ETN[13].

A VIX ETF is a marketable security that tracks a VIX futures index and trades like a common stock on a stock exchange. VIX ETFs seek investment results that track the performance of relevant underlying VIX futures indices by getting relevant positions in the component futures of their underlying indices. The payment made on VIX ETFs is based on the performance of the underlying index and then less the investor fee.

VIX ETNs are unsecured debt obligations that provide investors exposure to VIX futures market. In general, a VIX ETN tracks an underlying VIX futures index and seeks to replicate the performance of its underlying index. VIX ETNs are riskier than ordinary

[13] Most VIX ETFs and ETNs are traded on the Bats Global Markets (BATS) exchanges.

unsecured debt securities, since there is no principal protection for its investors and it is not an obligation of or guaranteed by any third party. Owning the ETNs is not the same as owning interests in the components of underlying index or a security directly linked to the performance of the underlying index. Instead, investors receive a cash payment at maturity or upon early redemption based on the performance of the underlying index and then less the investor fee. The payment made on a VIX ETN, including any payment at maturity or upon redemption, depends on the ability of its issuer to satisfy the obligations as they come due. The significant risks involved in VIX ETNs might make them only suitable for those sophisticated investors with necessary knowledge on how VIX ETNs work.

As discussed above, the way VIX ETFs and ETNs get the exposure could be quite different, even as they track the same VIX-related index. For instance, VIX ETFs which track the performance of the S&P 500 Short-Term VIX Futures Index own those VIX futures contracts comprising the underlying index. More specifically, as the S&P 500 Short-Term VIX Futures Index comprises VIX futures expiring in first and second front months, those VIX ETFs need to get long or short positions in VIX future contracts maturing in first- and second-front months, depending on the tracking strategies. VIX ETNs in contrast to VIX ETFs do not necessarily have holding positions, as an arrangement may be made with the issuing bank or an independent swap counterparty. Thus, VIX ETNs become more flexible as long as they manage to provide investors the exposure to the underlying indices.

In order to follow the performance of tracked VIX futures indices, VIX ETPs roll the relevant positions in the VIX futures market on daily basis. For instance, a VIX ETF which tracks the performance of the S&P 500 VIX Short-Term Futures Index, rolls the first front-month VIX futures to the second front month on a daily basis in equal fractional amounts, which means the VIX ETF shorts the nearest-month VIX futures and longs the next-month VIX futures. When VIX futures term structure is in a contango situation, costs are accrued each time when the VIX ETFs/ETNs roll their positions in corresponding VIX futures. On the other hand, a VIX ETF that rolls its daily positions by purchasing the nearest-month VIX futures and shorting the next-month VIX futures, benefits from a contango situation.

1.3 Literature review

The literature on the VIX index has evolved into several streams. The first stream focuses on the pricing and modeling of the VIX index, VIX futures and VIX options. Zhang and Zhu (2006) posit a stochastic variance model of the VIX evolution over time and develop a model for VIX futures. They find free parameters estimated from different periods over-price VIX future contracts on different levels. This topic has also been examined by Lin (2007) and Brenner, Shu and Zhang (2008). Lin (2013) applies the CBOE exponential and hump volatility functions with one- to three-factor models of the VIX evolution to examine the pricing for VIX options. He finds that hump volatility functions provide efficient out-of-sample valuation for most VIX put options, while exponential volatility functions present an effective choice as pricing models for VIX call options. Fernandes, Medeiros, and Scharth (2014), examine the time-series properties of the VIX index and find that the VIX index displays long-range dependence. They resort to both parametric and semiparametric heterogeneous autoregressive processes for modeling and forecasting purposes. They find supportive evidences that there is a negative relationship between the VIX index and the S&P 500 index return as well as a positive contemporaneous link with the volume of the S&P 500 index. Lin, Li, Luo and Chern (2016) develop a new stochastic volatility model which could be used to consistently price equity and VIX derivatives with efficient pricing procedure. Wang, Huang, Li and Bao (2016) propose a new model for VIX options pricing. They include factors such as mean-reversion, jumps, and stochastic volatility in their model and find that the mean-reverting logarithmic jump and stochastic volatility model serves as the best model in all the required aspect.

Second stream in the relevant literature examines the interaction between the VIX and VIX-related products. Shu and Zhang (2012) apply a modified Baek and Brock nonlinear Granger test and report evidence that both spot and futures prices react simultaneously to new information, supporting the information and price efficiency in the VIX futures market. Konstantinidi, Skiadopoulos and Tzagkaraki (2008) investigate whether the behavior of the implied volatility indices are predictable, and their results show that no models outperform the random walk model in an out-of-sample setting and that no economically significant profits can be attained. Nossman and Wilhelmson (2009) focus on testing the efficiency of the VIX futures market, and they point out that the risk premium adjusted futures price forecasts the movement direction for the VIX index well. Kanniainen, Lin and Yang (2014) use information on the VIX to improve the empirical performance of GARCH models for pricing options on the S&P 500 and find supporting evidence that non-affine models outperform affine models. Frijns, Tourani-Rad and Webb (2016) investigate the relation of causality between the VIX and its futures and find evidence of causality from VIX futures to the VIX index. Daigler, Dupoyet and Patterson (2014) examine the concavity adjustment for VIX futures. They demonstrate that the implied variance of VIX futures is strongly correlated with both market volatility and VIX futures time to expiration. Fu, Sandri, and Shackleton (2016) examine how the VIX spot, VIX futures and their basis perform different roles in asset pricing. They decompose the VIX index into volatilities calculated from out-of-the-money call options and volatility calculated from out-of-the-money put options separately, and find that out-of-the-money put options capture more useful information in predicting future stock returns. Chen and Tsai (2017) investigate the price discovery competition between the VIX and VIX futures and find that VIX futures prices play a dominant role in the overall process of price discovery. They also show that such dominant role of VIX futures is increased by the news announcements on macro-economic issues in the U.S. Kao, Tsai, Wang, and Yen (2018) examine the relation between trading activity in VIX derivatives markets and changes in the VIX index with high-frequency data and find that the signed trading variables of VIX futures are significantly related to the contemporaneous changes in the VIX index. Their findings also show the net signed trading variables of VIX futures are significant predictors of future changes in the VIX index.

Another stream in the VIX literature analyzes VIX ETPs. Husson and McCann (2011) assess the risks associated with the VXX ETNs, and show that the return to the VXX ETNs depends in large part on movements in the futures markets. Stanton (2011) and Deng, McCann and Wang (2012) investigate how effectively VIX ETPs can hedge a portfolio of U.S. large-cap stocks and find that VIX ETPs can hardly be applied as an effective hedging instrument. Alexander and Korovilas (2012) study the return of VIX ETNs and argue that the ETN market could lead VIX futures despite the fact that they are supposed to track. They document that the large-scale hedging activities of ETN issuers on the CBOE market could affect the prices of VIX futures. The VIX ETN issuers who have a short position in volatility need to hedge it with a long position in volatility-linked products such as VIX futures. The popularity of ETNs leads to an increased need for hedging, which may result in upward pressure on VIX futures. The pressure may even be amplified by the fact that speculative traders can predict ETNs hedging activity and front-run them by taking a long position on CBOE VIX futures. A similar topic has been examined by Eraker and Wu (2014), who propose an equilibrium model to explain the negative expected return to VIX futures and ETNs. Clowers and Jones (2016) investigate eight VIX ETPs that include ETNs and ETFs. They compare the performance and returns of those VIX instruments with that of the VIX index and report that VIX ETPs do not correlate well with the VIX index. They further suggest that VIX ETPs are not suitable for a buy-and-hold investment strategy, as those ETPs are exposed to a declining value, due to the large degree of contango in VIX futures applied by these ETPs. Gehricke and Zhang (2017) develop a theoretical model which links the S&P500 index, VIX and VIX short-term futures ETNs to test the VXX ETN. They find that roll yield of VIX futures, which is mostly a negative process, drives the difference between the VXX and VIX returns. Bordonado, Molnár, and Samdal (2017) test the performance of VIX ETPs and find evidences that VIX ETPs perform poorly as a hedging tool. They also show that including VIX ETPs in a portfolio based on S&P 500 will decrease the risk-adjusted performance of the portfolio. Fernandez-Perez, Frijns, Gafiatullina, and Tourani-Rad (2016) investigate the intraday price discovery between the VIX short-term futures ETNs and inverse VIX short-term ETNs. They find strong time variation in the price discovery contribution between these two VIX ETNs, and trading costs and market liquidity are the significant determinants of price discovery. Their findings also show that the price discovery of VIX ETN increases with the higher institutional ownership.

1.4 Hypothesis

The following section summarizes the hypothesis on the fund flows to different VIX ETPs and how the flows impact on the VIX index. I also elaborate on other factors, such as VIX futures prices and VIX futures price term structure, and discuss their possible effects on the VIX index.

1.4.1 Fund flow to VIX ETPs

As VIX ETPs are structured to generate returns when the equity volatility changes, investors tend to include more VIX ETPs in their portfolios to hedge against market volatility, especially when the stock market performs poorly. Makan and Kaminska (2012) argue that with the increased popularity of VIX ETPs, a greater amount of money flows into those volatility-related investment vehicles. In order to accommodate the increased money flows and provide investors with more exposure to market volatility, VIX ETPs tend to open more positions in the VIX futures market to track the performance of the underlying VIX futures indices. These trades in the VIX futures market by VIX ETPs are generally large; therefore, they might distort the price of VIX futures. The imbalance in VIX futures could then seep into the underlying S&P options market and affect the VIX index. On the other hand, VIX ETPs provide different tracking strategies (normal or inverse),[14] and thereby can generate quite different returns, depending on the prevailing market conditions. For instance, when equity market volatility increases, a VIX ETP which applies the normal tracking strategy generates a positive return, while a VIX ETP applying the inverse tracking strategy loses money. On the contrary, when stock market volatility decreases, a VIX ETP

[14] A VIX ETP which applies a normal strategy provides exposure to the performance of its underlying index, while a VIX ETP which applies an inverse strategy provides exposure to the inverse performance of its underlying index.

applying the normal tracking strategy suffers a loss, whereas a VIX ETP applying the inverse tracking strategy gains profit. As funds could flow into VIX ETPs which employ different tracking strategies under different market conditions, the impacts of fund flows to the normal and inverse tracking strategy VIX ETPs may offset each other. Thus, it is not clear if the aggregated fund flows to all VIX ETPs has any statistically significant overall impacts on the VIX index.

As discussed above, investors have various incentives to invest in VIX ETPs which employ different tracking strategies. In order to isolate the impacts of fund flows to different categories of VIX ETPs, I divide VIX ETPs into separate groups depending on their tracking strategies (normal and inverse) and the horizons of their underlying future indices (short-term and mid-term). This allows me to test the impacts of fund flows to different VIX ETP groups, namely normal-short, normal-mid and inverse-short. When there are increasing fund flows to VIX ETPs in normal-short and normal-mid groups, those VIX ETPs tend to get more long positions in relevant VIX futures, lifting up the prices of VIX futures. An increase in VIX futures prices will imply a higher expected value of the VIX index. Therefore, I hypothesize that the fund flows in VIX ETPs in normal-short and normal-mid groups have positive impacts on the VIX index. Analogously, higher fund flow to VIX ETPs in inverse groups leads those VIX ETPs to short more relevant VIX futures, pulling down the VIX future prices and the expectation for market volatility in the future. I put forward the hypothesis that fund flows to inverse VIX ETP groups have negative impacts on the VIX index.

In addition, taking into account the mean-reverting property of the VIX index (Dueker, 1997; Whaley, 2008; Leung, Li, and Wang, 2016), it is likely that investors get more incentives to trade VIX ETPs during time periods when equity market volatility is extreme (high or low). More specifically, investors are motivated to take long positions in VIX ETPs in normal (inverse) groups when the VIX index is extremely low (high). In such a case, investors expect the VIX will move in a mean-reverting way and therefore speculate the future movement of the index by investing more money in VIX ETPs. Consequently, the higher fund flow to VIX ETPs is likely to put pressure on the VIX since VIX ETPs need to take more positions in VIX futures. On the other hand, the collapse of equity markets' value is generally accompanied by important market events, which might outperform investors' perception of the mean-reversion about the VIX. In that case, the VIX index is more likely influenced by the market trends. Thus, the impacts of fund flow to VIX ETPs on VIX during such periods might have an unclear pattern. I expect investors have more incentives and are more likely to take more speculative positions when the VIX is high. Therefore, I hypothesize that during the period when equity market volatility is extreme, the impact of fund flow to VIX ETPs' inverse and normal groups on the VIX index is stronger.

1.4.2 VIX futures price and VIX futures price term structure

Previous literature has widely investigated the relationship between the VIX index and VIX futures. Some studies report the information and price efficiency in the VIX futures market (Konstantinidi, Skiadopoulos and Tzagkaraki, 2008; Shu and Zhang, 2012). On the other hand, there are studies showing VIX futures prices can forecast the movement direction of the VIX index (Nossman and Wilhelmson, 2009; Frijns, Tourani-Rad and Webb, 2014). In line with the previous studies, I include lagged VIX futures price change in the model to account for the potential predictable effect of VIX futures on the VIX index and, in addition, control for the autocorrelation effects in the VIX index. Accordingly, the lagged VIX futures price change is expected to have a positive impact on the VIX index.

The term structure of VIX futures is typically in contango (upward sloping) and changes into backwardation (downward sloping) when the equity market moves into excessively volatile periods (Alexander and Korovilas, 2012). Recall that a contango (backwardation) term structure refers to a market condition where the longer-term futures contract is trading at a higher (lower) price than the nearer-term futures contract, therefore reflecting the market expectation for a future spot price (Gorton and Rouwenhorst, 2005). I include a measure of the VIX futures term structure in the model to capture the market's expectation of the VIX index. Accordingly, a backwardation term structure is expected to have a negative effect on the level of the VIX index.

1.5 Data and Method

1.5.1 Data

The sample includes 1387 daily observations of VIX ETFs and ETNs traded on U.S. exchanges. The sample period spans from 28 January 2009, when the first VIX ETP was issued, to 31 December 2015. The daily closing data for the S&P 500 index, VIX index, VIX futures term structure and fund flows to VIX ETPs were collected

Table 1.1 Characteristics of ETFs and ETNs

Name	Ticker	Market Cap (in millions)	Tracking Strategy	Fund Type	Inception Date	Underlying Index	Price	Expense Ratio	Turnover (in millions)
AccuShares Spot CBOE VIX Down Shares	VXDN	3.50	Inverse	ETF	5/19/2015	CBOE Volatility Index (VIX)	15.00	0.95%	0.009
AccuShares Spot CBOE VIX Up Shares	VXUP	2.77	Normal	ETF	5/19/2015	CBOE Volatility Index (VIX)	12.30	0.95%	0.018
ETRACS Daily Long-Short VIX ETN	XVIX	11.96	Normal	ETN	11/30/2012	S&P 500 Index VIX Term-Structure Excess Return	15.60	0.85%	0.028
First Trust CBOE S&P 500 VIX Tail Hedge Fund	VIXH	3.63	Normal	ETF	8/30/2012	CBOE VIX Tail Hedge Index	21.77	0.60%	0.018
iPath Inverse S&P 500 VIX Short-Term Futures ETN	XXV	0.75	Inverse	ETN	7/16/2010	S&P 500 VIX Short-Term Future Index	38.04	0.89%	0.008
The iPath S&P 500 Dynamic VIX ETN	XVZ	9.16	Normal	ETN	8/17/2011	S&P 500 Dynamic VIX Futures TR Index	27.27	0.95%	0.074
iPATH S&P 500 VIX Mid-Term Futures ETN	VXZ	38.43	Normal	ETN	1/29/2009	S&P 500 Mid-Term VIX Futures TR Index	13.04	0.89%	13.966
iPath S&P 500 VIX Short-Term Futures ETN	VXX	760.71	Normal	ETN	1/29/2009	S&P 500 Short-Term VIX Futures TR Index	27.52	0.89%	2945.351
ProShares Short VIX Short-Term Futures	SVXY	628.10	Inverse	ETF	10/4/2011	S&P 500 Short-Term VIX Futures Index	33.92	0.95%	384.764
ProShares Ultra VIX Short-Term Futures	UVXY	565.67	Twice	ETF	10/2/2011	S&P 500 Short-Term VIX Futures Index	49.63	0.95%	1543.228
ProShares VIX Mid-Term Futures ETF	VIXM	27.66	Normal	ETF	1/4/2011	S&P 500 Mid-Term VIX Futures Index	63.34	0.85%	1.475
ProShares VIX Short-Term Futures ETF	VIXY	105.97	Normal	ETF	1/4/2011	S&P 500 Short-Term VIX Futures Index	18.24	0.85%	72.812
VelocityShares Daily 2x VIX Medium Term ETN	TVIZ	1.53	Twice	ETN	11/29/2010	S&P 500 Mid-Term VIX Futures Index	18.81	1.65%	0.006
VelocityShares Daily 2x VIX Short Term ETN	TVIX	299.24	Twice	ETN	11/29/2010	S&P 500 Short-Term VIX Futures Index	10.89	1.65%	431.748
VelocityShares Daily Inverse VIX Medium Term ETN	ZIV	103.81	Inverse	ETN	11/29/2010	S&P 500 Mid-Term VIX Futures Index	34.53	1.35%	1.541
VelocityShares Daily Inverse VIX Short-Term ETN	XIV	1012.11	Inverse	ETN	11/29/2010	S&P 500 Short-Term VIX Futures Index	17.37	1.35%	658.270
VelocityShares VIX Medium Term ETN	VIIZ	0.62	Normal	ETN	11/29/2010	S&P 500 Mid-Term VIX Futures Index	17.81	0.89%	0.007
VelocityShares VIX Short Term ETN	VIIX	9.38	Normal	ETN	11/29/2010	S&P 500 Short-Term VIX Futures Index	37.26	0.89%	11.148

This table presents an overview of the prevailing VIX exchange-traded funds and VIX exchange-traded notes (sourced from Bloomberg on 31 December 2015). The *tracking strategy* indicates how exchange-traded products provide investors with a cash payment at the scheduled maturity or early redemption. For instance, a *Twice* tracking strategy indicates that the exchange-traded fund (note) will provide its investors with a cash payment at the scheduled maturity or early redemption based on 2X the performance of its underlying index. *Turnover* is defined as Turnover / Traded Value according to Bloomberg, which represents the sum of all trade prices, multiplied by the number of shares related to each price.

from the Bloomberg database. The sample covers close to 100% of total market capitalization of all VIX-related ETPs. The descriptive information for those VIX ETPs is presented in Table 1.1.

As presented, there are 18 VIX ETFs and ETNs, and 13 of them track the S&P 500 short-term or mid-term VIX futures indices. Among these 13 VIX ETPs, there are four VIX ETFs issued by Proshares, while the other nine are VIX ETNs.

1.5.2. Method

To examine the effect of VIX ETPs fund flows on the VIX index, the following model was estimated:

$$R_t^{VIX} = \beta_0 + \sum_{i=1}^{k} \varphi_1 Flow_{i,t-1} + \beta_1 R_{t\text{-}1}^{VF} + \beta_2 Down_t + \beta_3 Flow_{i,t-1} \cdot Down_t + \beta_4 \Delta CB17_t + \varepsilon_{i,t} \quad (1.1)$$

where:

R_t^{VIX} is the percentage change in the daily closing price of the underlying VIX index at the end of day *t*.

$Flow_{i,t-1}$ is the lagged net fund flow to group *i* (*i*=1,…, *k*). *k* indicates the number of VIX ETP groups examined in each model specification.

$R_{t\text{-}1}^{VF}$ is the lagged percentage change in the daily price of VIX futures.

$CB17_t$ is the VIX futures term structure proxy, which is calculated as the price difference between the first front month and the seventh front month VIX futures, then divided by the first front-month VIX future price[15].

[15] The other term structure measure designed to capture the backwardation effect was considered. The results were robust for selection of the backwardation proxy. When I consider the proxy for backwardation in the VIX futures price term structure, there is a tradeoff between measure length, which captures the number of future months in term structure, and data availability, as there are periods when the price of VIX futures for longer than eight months is not available. Hence, CB17 is applied as the

$\Delta CB17_t$ is the change in VIX futures term structure calculated as the difference between $CB17_t$ and $CB17_{t-1}$[16].

$Down_t$ is the time dummy, which equals to one when the daily return of the S&P 500 index is lower than its fifth percentile level observed during the study period. Both the first and fifth percentile are in line with the method to estimate Value at Risk (see Jorion, 2007). However, selection of the first percentile results in a low number of trading days.

$Flow_{i,t-1} \cdot Down_t$ is the interaction of the lagged fund flow and the time dummy, which captures the impact of the fund flow to VIX ETPs during market turmoil periods.

$\varepsilon_{i,t}$ is the error term. For the sake of completeness, I include the definitions and descriptive statistics of all variables employed in the chapter (see Table 1.2).

1.6 Empirical Results

1.6.1 Descriptive statistics

In this section, I first examine the changes in net fund flows to VIX ETPs during the study period. The S&P 500 index returns are employed to proxy for various

proxy for backwardation and it measures a relatively long period (seven months) in term structure, and thus provides data consistency. In the robustness test, I also apply different length measures, such as CB15, which is the ratio calculated with the first and fifth front-month VIX future prices in term structure, and I get similar findings.

16 $\Delta CB17_t$ is defined as: $\Delta CB17_t = \frac{(P_{1,t} - P_{7,t})}{P_{1,t}} - \frac{(P_{1,t-1} - P_{7,t-1})}{P_{1,t-1}} = \frac{P_{7,t-1}}{P_{1,t-1}} - \frac{P_{7,t}}{P_{1,t}}$, where $P_{i,t}$ is the price of i^{th} front month VIX future at time t. A high positive value of $\Delta CB17_t$ indicates that VIX future term structure changes from strong contango to deep backwardation.

Table 1.2 Summary statistics for models' variables

Variables	Definition	Obs	Mean	Std. Dev.	Min	Max	Median	10% Percentile	90% Percentile
ChgVIX	Daily percentage change of VIX Index	1926	0.0025	0.0755	-0.2957	0.5000	-0.0063	-0.0760	0.0898
ΔVFX	Daily percentage change of generic 1st VIX future	1926	0.0012	0.0532	-0.2081	0.3098	-0.0067	-0.0539	0.0672
netfflow	Aggregated net fund flow of all VIX ETFs	1672	7.0900	72.5425	-552.2840	611.3002	0.5452	-59.5922	81.5903
inverse_etf_flow	Aggregated net fund flow of all inverse VIX ETFs	1672	0.2548	33.3681	-269.4550	449.1380	0.0000	-17.5230	17.0538
normal_etf_flow	Aggregated net fund flow of all normal VIX ETFs	1672	6.7279	70.3366	-552.2840	424.5397	1.5200	-59.7276	79.3109
normal_short	Aggregated net fund flow of all normal-short VIX ETFs	1672	6.4116	66.9742	-362.5740	418.8950	0.3515	-56.7439	74.9697
normal_mid	Aggregated net fund flow of all normal-mid VIX ETFs	1672	0.3163	18.9778	-375.0530	150.1380	0.0000	-3.4139	5.7396
inverse_short	Aggregated net fund flow of all inverse-short VIX ETFs	1388	0.2712	37.7301	-269.4550	449.1380	0.0000	-25.6501	22.9747
inverse_mid	Aggregated net fund flow of all inverse-mid VIX ETFs	960	0.0751	1.2349	-12.7828	13.6158	0.0000	0.0000	0.0000
CB17	Term structure factor calculated as the ratio of price difference between first front month and 7th front month VIX future over the first front month VIX future price ($Price_1$-$Price_7$)/$Price_1$	1913	-0.1763	0.1951	-0.8055	0.5121	-0.2055	-0.3925	0.0954
ΔCB17	Change in term structure factor, calculated as $CB17_t$-$CB17_{t-1}$	1913	-.0001	0.0493	-0.2414	0.3501	-0.0054	-0.0492	0.0545
Down	Time Dummy equals to one when the return of S&P 500 index is lower than its fifth percentile level during the study period	1927	0.050337	0.218697	0	1	0	0	0

This table presents the definition and statistical summary of the variables employed in the models. The most traded VIX ETF groups are the normal-short and inverse-shot groups, which have the highest market capitalization and high net fund flows.

market conditions. I categorize the S&P 500 index returns into deciles and record the statistics of the net fund flow to each of the four examined VIX ETP groups in each decile. Table 1.3 presents the mean and standard deviation of net fund flows to normal-short, normal-mid, inverse-short and inverse-mid VIX ETPs across the range of the S&P 500 index returns observed during the study period.

As depicted in Panel A, on average, there are positive fund inflows to all four VIX ETP groups. The normal-short group received the highest daily average flow of $6.14 million, whereas the inverse-mid group, being newly established, experienced the smallest daily average fund inflow of $0.07 million. The net fund flow into the normal-short group peaked at normal market conditions, with the daily average reaching $17.8 million when the S&P 500 index returns hovered around its fifth decile. In contrast, the fund flow to the inverse-short group reached its highest levels over the periods when the S&P 500 index experienced extreme returns, with the daily average flow of $14.4 million recorded in the lowest decile and $12.5 million in the highest decile of the S&P 500 index returns.

As presented in Panel B of Table 1.3, the fund flow to the normal-short group was more volatile than those of other groups, as evidenced by a higher standard deviation. It is noteworthy that the fund flow to the inverse-short group is characterized by the highest variability when the S&P 500 index experienced extremely negative returns.

Figure 1.4 features the 25th percentile, 75th percentile, mean and median of the fund flows for three large groups (normal-short, normal-mid, inverse-short) across the range of S&P 500 index returns. The observed flows for normal-short and inverse-short VIX ETPs follow distinct patterns, and are consistent with the statistics presented in Panel A of Table 1.3.

Table 1.3 Return of S&P 500 and net fund flow to VIX ETPs

Panel A (Mean)

Groups	Mean	1-10th (Low)	11-20th	21-30th	31-40th	41-50th	51-60th	61-70th	71-80th	81-90th	91-100th (High)
Normal Short	6.144	2.9608	-7.2581	3.3666	8.5051	17.8095	16.6448	14.6465	9.6549	-3.6180	-9.3570
Normal Mid	0.303	-0.7874	0.7841	0.3631	1.1774	0.5076	-0.6478	1.4473	0.5959	-1.2884	0.4106
Inverse Short	0.259	14.4328	7.0322	-0.4519	-4.2615	-6.1165	-4.1646	-0.9423	0.2431	0.6202	12.5098
Inverse Mid	0.071	-0.3180	-0.2568	0.1122	-0.0366	0.0956	0.1454	0.2082	0.1133	0.4690	-0.2360

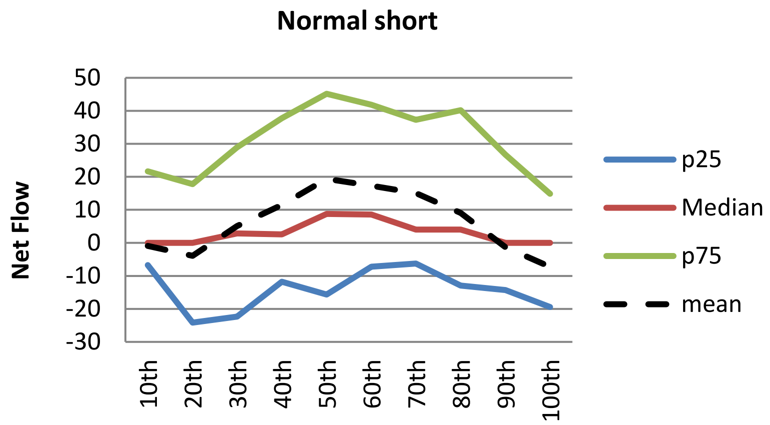
Panel B (Std. Dev.)

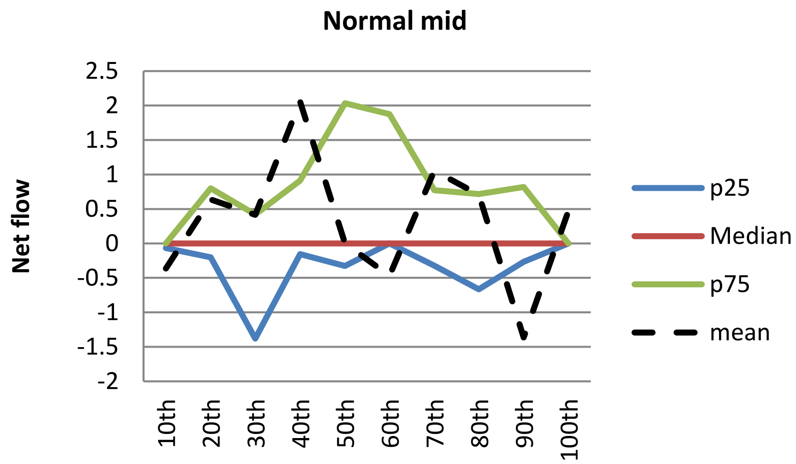
Groups	Std Dev.	1-10th (Low)	11-20th	21-30th	31-40th	41-50th	51-60th	61-70th	71-80th	81-90th	91-100th (High)
Normal Short	65.589	71.9578	63.6202	69.6233	64.9948	67.8106	67.5709	53.1456	59.1076	69.5805	77.7791
Normal Mid	18.582	23.1616	17.2052	8.0741	6.8775	31.4368	29.4577	13.1752	7.7786	21.8894	12.1082
Inverse Short	36.904	63.7158	40.0727	24.7741	34.5564	41.8283	29.1457	18.0659	38.0640	41.8319	34.7234
Inverse Mid	1.205	1.3906	1.5245	0.9973	1.2775	0.8434	1.3527	1.4125	0.3725	1.7388	1.0949

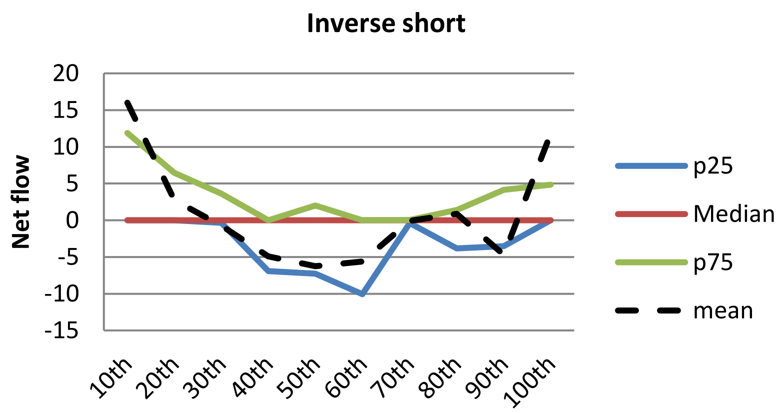
This table presents the summary statistics for net fund flows to four exchange-traded funds and notes groups: normal-short group, normal-mid group, inverse-short group and inverse-mid group. The net fund flows are summarized based on the different deciles of S&P 500 index returns, Panel A presents the means of net fund flows and Panel B presents the standard deviation of net fund flows for four VIX ETF/ETN groups. Panel A shows the net fund flow into the normal-short group peaked at the fifth decile of S&P 500 index returns, while the fund flow to inverse-short group achieved its highest levels over the periods when the S&P 500 index experienced extreme returns. In Panel B, higher standard deviation levels can be observed over the periods when the S&P 500 index experienced extreme returns for both normal and inverse VIX ETF groups.

Figure 1.4

This figure presents the 25th percentile (p25), 75th percentile (p75), mean and median of the fund flows at different deciles of the daily returns of the S&P 500 index. The horizontal axis indicates the level of the daily returns of the S&P 500 index from decile 1 to decile 10.



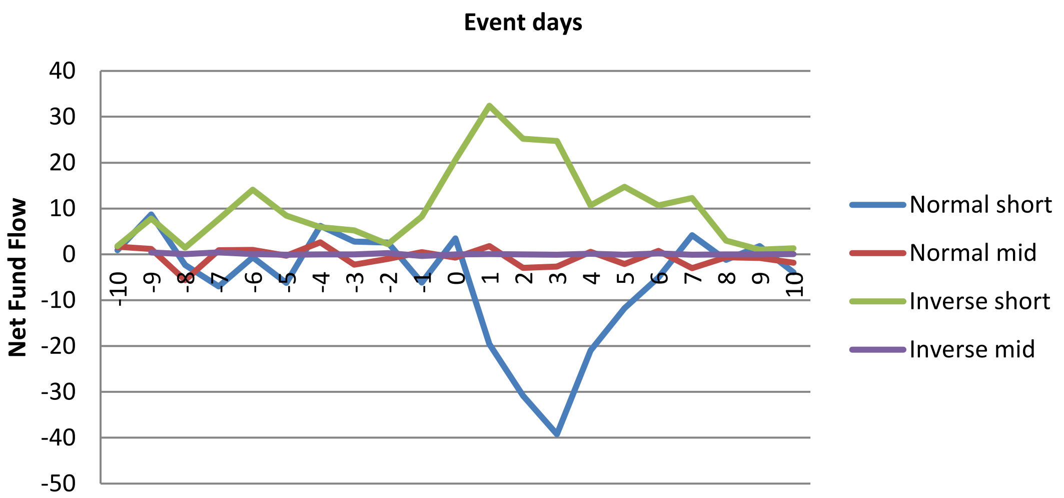




An interesting question is how the net fund flow to VIX ETP groups changed over the periods of market turmoil. I define market turmoil as the periods when the S&P 500 index returns fell below its fifth percentile level observed during the study period.

Figure 1.5 depicts the changes in the average net flows to the four VIX ETP groups for 10 days prior to and after day “0”, marked as when the S&P 500 index fell below its fifth percentile level of -1.5%. There are 78 days with such extremely negative returns during the study period.

Figure 1.5



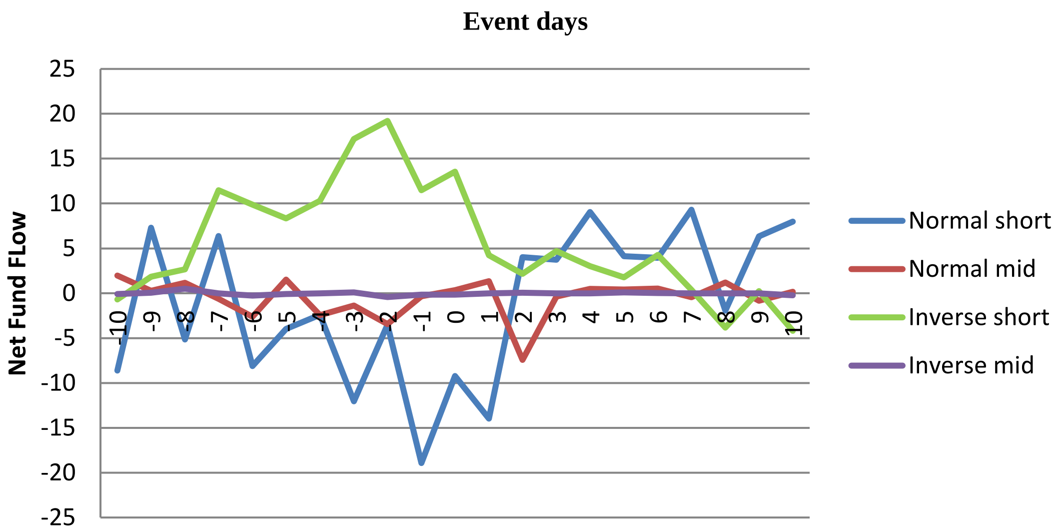
This figure presents the changes in the average net flows to the four VIX ETF/ETN groups for 10 days before and after the days when the daily return of the S&P 500 index fell lower than -1.5%, which is around the fifth percentile level of the S&P 500 index daily returns observed during the study period. Axis X presents the event days where day "0" is the day when the S&P 500 index fell below -1.5%. There are 78 days with extremely negative returns as defined above.

As shown in Figure 1.5, a high net fund flow to inverse-short group was accompanied with an outflow of money from normal-short group. The pattern suggests that in time when equity market experienced extremely negative returns, investors bet that observed high volatility will go down. In such a case, it’s likely that normal-short

VIX ETPs will make loss while inverse-short ETPs will generate positive returns. This pattern supports the argument that market participants expect the VIX index to move in a mean-reverse way (Whaley, 2008; Leung, Li, and Wang, 2015).

Figure 1.6 shows the changes in the average net flows to the four ETP groups for 10 days before and after the days when the S&P 500 index recorded a higher return than its 95th percentile level of 1.5%. There are 72 days with such extremely positive returns during the study period

Figure 1.6



This figure presents the changes in the net flows to the four VIX ETF/ETN groups for 10 days before and after the days when the daily return of the S&P 500 index was higher than 1.5 percent, which is around the 95th percentile level of the S&P 500 index daily returns observed during the study period. Axis X presents the event days where day "0" is the day when S&P 500 index rose above 1.5 percent. There are 72 days of extremely positive returns as defined above.

As presented in Figure 1.6, there was a large inflow to the inverse-short group and a substantial outflow from the normal-short group prior to day “0”. The trading died down later after the boom days. That’s to say, when the market performs well the patterns of the fund flow to inverse-short and normal-short groups indicate that investors expect a higher volatility. I conjecture that investors anticipate an increase in the VIX as a result of a market correction following a surge of more than 1.5 percent. However, the patterns observed in Figure 1.6 are not as striking as those featured in Figure 1.5.

As a robustness check, I use the VIX index value as an alternative proxy for market performance. Table 1.4 presents the summary statistics of the net fund flows to the four VIX ETP groups across different deciles of the VIX index values. Panel A presents the means of net fund flows and Panel B presents the standard deviation of net fund flows for the four VIX ETP groups. As seen in Panel A, the normal-short group experienced the largest inflow of $28.9 million when the VIX index was in its lowest decile, and saw the largest outflow of $15.48 million when the VIX index reached its highest decile level. In contrast, the net fund flow to the inverse-short group saw a deep inflow of $24.7 million when the VIX index recorded its highest decile level, and experienced the largest outflow of $10.1 million when the VIX index plunged to its lowest decile level. As shown in Panel B of Table 1.4, the inverse-short group has the most volatile net fund flow and it occurred when the VIX index peaked at its top decile.

Overall, the above findings suggest that investors tend to take long positions in normal (inverse) VIX ETP groups over normal (volatile) market conditions. The observed patterns were more pronounced during the 10-day window surrounding the days with extreme returns.

Table 1.4 VIX Index and net fund flow to VIX ETPs

Panel A (Mean)

Groups	Mean	1-10th (Low)	11-20th	21-30th	31-40th	41-50th	51-60th	61-70th	71-80th	81-90th	91-100th (High)
Normal Short	6.144	20.8711	23.8792	16.5448	-5.7747	6.4720	0.7122	7.3500	-1.4035	-3.6672	-15.4757
Normal Mid	0.303	0.0598	0.0690	1.9308	1.4822	-0.9409	2.3011	3.0507	-2.6055	-2.7668	0.4309
Inverse Short	0.259	-10.1255	-12.2512	-1.9216	5.0251	3.4684	8.4641	3.8806	12.3259	8.1191	24.6975
Inverse Mid	0.071	0.2060	0.1960	0.1626	-0.1040	0.0231	-0.1390	-0.2741	0.0000	0.0000	0.0000

Panel B (Std. Dev.)

Groups	Std Dev.	1-10th (Low)	11-20th	21-30th	31-40th	41-50th	51-60th	61-70th	71-80th	81-90th	91-100th (High)
Normal Short	65.589	55.7746	65.5432	78.2627	56.7149	78.8435	72.5231	57.8501	48.7249	63.2013	77.3060
Normal Mid	18.582	3.5386	5.8124	10.9495	15.3976	32.0663	11.8551	17.4937	22.9096	33.8211	6.3830
Inverse Short	36.904	36.9685	42.4271	37.1539	31.6322	22.6499	21.7533	23.4654	46.7610	35.8846	97.0481
Inverse Mid	1.205	1.6817	1.1825	1.3257	0.7952	0.2543	1.0269	1.7397	0.0000	0.0000	0.0000

This table presents the summary statistics for net fund flows to four exchange-traded funds and notes groups: normal-short group, normal-mid group, inverse-short group and inverse-mid group. The net fund flows are summarized based on the different deciles of VIX index. Panel A presents the means of net fund flows and Panel B presents the standard deviation of net fund flows for four VIX ETF/ETN groups. Panel A indicates that the net fund flow to the normal-short group gets its highest positive level when the VIX index is low and the heaviest outflow appears when the VIX index is high, while the net fund flow to inverse-short group shows an opposite trend – deep inflow (outflow) when the VIX index value is high(low). In Panel B, standard deviation of fund flows is found to be higher at the two ends of the distribution for the inverse-short VIX ETF group.

1.6.2 Estimation model

In order to address the concern that some of the independent variables may be correlated, I present the matrix in Table 1.5.

To examine the effects of the fund flows to VIX ETPs on the VIX index value, I run three sets of models, each with different specifications. First, I analyze the aggregated fund flow to all VIX ETPs; the results are presented in Table 1.6. I then categorize VIX ETPs into two groups based on their tracking strategies (normal or short) and conduct a similar analysis. The results are presented in Panel A of Table 1.7. I further categorize VIX ETPs into three groups based on both the tracking strategies (normal or short) and the horizon of their underlying indices (short-term or mid-term). The results are presented in Panel B of Table 1.7. In all analyses, the parameters estimation is reported with Newey-West standard errors.

The results in Table 1.6 indicate that the aggregated fund flow to all VIX ETPs has no statistically significant impacts on the VIX index, even during market turmoil periods. On the other hand, the time dummy, which captures the periods with extremely negative returns, and the shift in VIX future price term structure, exhibits significant positive effect on the VIX index. A higher $\Delta CB17_t$ is associated with a more pronounced shift in VIX futures term structure from contango to backwardation. The results suggest that a higher VIX index value is more likely to occur when the equity market plunges to its lowest 5 percent level and when the VIX futures term structure changes to backwardation from contango. The lagged VIX futures price change has significant negative impacts on the VIX index change.

Table 1.5 Correlation matrix for model variables

	$ChgVIX_t$	ΔVFX_{t-1}	$Down_t$	$\Delta CB17_t$	$normal\_short_{t-1}$	$normal\_mid_{t-1}$	$inverse\_short_{t-1}$	$inverse\_mid_{t-1}$
$ChgVIX_t$	1.0000							
ΔVFX_{t-1}	-0.0650**	1.0000						
$Down_t$	0.5153***	0.0221	1.0000					
$\Delta CB17_t$	0.7056***	-0.0254	0.3490***	1.0000				
$normal\_short_{t-1}$	0.0402	0.0390	-0.0452*	0.0125	1.0000			
$normal\_mid_{t-1}$	0.0312	-0.0315	0.0110	0.0290	0.0108	1.0000		
$inverse\_short_{t-1}$	-0.0675**	0.0455*	0.0631**	-0.0137	-0.2182***	0.0089	1.0000	
$inverse\_mid_{t-1}$	-0.0163	-0.0379	-0.0640**	-0.0132	0.0143	0.0359	0.0227	1.0000

Table 1.5 presents the correlation between the independent variables employed in the estimation models. *,**,*** corresponds to statistically significance at the 10 percent, 5 percent and 1percent level, respectively.

Table 1.6
The impact of aggregated money flow to VIX ETPs on the VIX index

	(1)	(2)	(3)	(4)
Aggr Fund Flow$_{t-1}$	0.0135	0.0212	0.0014	0.0096
	(0.43)	(0.78)	(0.07)	(0.51)
Down$_t$* Aggr Fund Flow $_{t-1}$		-0.0572	0.0891	-0.0006
		(-0.23)	(0.25)	(-0.00)
ΔVFX$_{t-1}$	-0.0938*	-0.1110***	-0.0669*	-0.0816**
	(-1.79)	(-2.74)	(-1.76)	(-2.54)
Down$_t$		0.1817***		0.1082***
		(12.30)		(8.69)
ΔCB17 $_t$			1.0630***	0.9002***
			(12.93)	(12.33)
Adj R-squared	0.003	0.2698	0.5827	0.5824
Observations	1387	1387	1387	1387

The dependent variable is the daily percentage change of the VIX index value. The main explanatory variable is aggregated fund flow of all VIX-related exchange-traded funds and notes. ΔVFX_{t-1} is the percentage change in the daily price of VIX futures with a one-day lag; $CB17_t$ is the VIX futures term structure item, calculated as the ratio of price difference between the first front-month and seventh front-month VIX future over the first front-month VIX future price; $\Delta CB17$ is defined as the change in VIX futures term structure item, calculated as the difference between $CB17_t$ and $CB17_{t-1}$; $Down_t$ is the time dummy, which equals to one when the return of the S&P 500 index is lower than its fifth percentile level during the study period. The columns in Table 1.6 report the findings with different controls. *t*-statistics are reported in brackets. *,**,*** corresponds to statistically significance at the 10%, 5% and 1% level, respectively.

Table 1.7 Panel A
The impact of money flow to VIX ETPs on the VIX index

	(1)	(2)	(3)
Normal Fund Flow $_{t-1}$	0.0369	0.0537**	0.0400**
	(1.17)	(1.98)	(2.42)
Inverse Fund Flow $_{t-1}$	-0.1134*	-0.1697***	-0.1582***
	(-1.76)	(-3.45)	(-3.93)
Down $_{t}$ * Normal Fund Flow $_{t-1}$			-0.0731
			(-0.26)
Down $_{t}$ * Inverse Fund Flow $_{t-1}$			0.3470
			(0.80)
ΔVFX$_{t-1}$	-0.0910*	-0.1064***	-0.0821***
	(-1.70)	(-2.58)	(-2.62)
Down $_{t}$		0.1840***	0.1067***
		(12.19)	(8.14)
ΔCB17$_{t}$			0.8932***
			(12.24)
Observations	1387	1387	1387
Adj R-squared	0.0075	0.2813	0.5907

The dependent variable is the daily percentage change of the VIX index value.$\Delta VFX_{t-1}$is the percentage change in the daily price of VIX futures with a one-day lag; $CB17_t$ is the VIX futures term structure item, calculated as the ratio of price difference between the first front-month and seventh front-month VIX future over the first front-month VIX future price; $\Delta CB17$ is defined as the change in VIX futures term structure item, calculated as the difference between $CB17_t$ and $CB17_{t-1}$; $Down_t$ is the time dummy, which equals to one when the return of the S&P500 index is lower than its fifth percentile level during the study period. By dividing all VIX ETFs and ETNs into different groups according to their different tracking strategies, Column (1), (2) and (3) present the results of Newey West tests based on two VIX ETF groups: the normal and inverse groups *t*-statistics are reported in brackets.*,**,*** corresponds to statistically significance at the 10%, 5% and 1% level, respectively.

Table 1.7 Panel B
The impact of money flow to VIX ETPs on the VIX index

	(4)	(5)	(6)
Normal Short Flow $_{t-1}$	0.0315	0.0503*	0.0386**
	(0.96)	(1.79)	(2.24)
Normal Mid Flow $_{t-1}$	0.1512*	0.1199	0.0641
	(1.69)	(1.42)	(1.07)
Inverse Short Flow $_{t-1}$	-0.1154*	-0.1721***	-0.1601***
	(-1.77)	(-3.46)	(-3.94)
Down $_{t}$ * Normal Short Flow $_{t-1}$			-0.0418
			(-0.14)
Down $_{t}$ * Normal Mid Flow $_{t-1}$			-1.3581
			(-1.01)
Down $_{t}$ * Inverse Short Flow $_{t-1}$			0.3671
			(0.85)
ΔVFX_{t-1}	-0.0895*	-0.1055**	-0.0799***
	(-1.66)	(-2.54)	(-2.61)
Down $_{t}$		0.1839***	0.1078***
		(12.17)	(8.07)
$\Delta CB17_{t}$			0.8927***
			(12.25)
Observations	1387	1387	1387
Adj R-squared	0.0073	0.2810	0.5910

The dependent variable is the daily percentage change of the VIX index value.$\Delta VFX_{t-1}$is the percentage change in the daily price of VIX futures with a one-day lag; $CB17_t$ is the VIX futures term structure item, calculated as the ratio of price difference between the first front-month and seventh front-month VIX future over the first front-month VIX future price; $\Delta CB17$ is defined as the change in VIX futures term structure item, calculated as the difference between $CB17_t$ and $CB17_{t-1}$; $Down_t$ is the time dummy, which equals to one when the return of the S&P500 index is lower than its fifth percentile level during the study period. By dividing all VIX ETFs and ETNs into different groups according to their different tracking strategies, Column (4), (5) and (6) present the results of Newey West test based on three[*] VIX ETF groups: the normal-short, normal-mid and inverse-short groups. *t*-statistics are reported in brackets.*,**,*** corresponds to statistically significance at the 10%, 5% and 1% level, respectively.

[*]According to different tracking strategies, there are four VTX ETF groups: normal-short, normal-mid, inverse-short and inverse-mid. The inverse-mid group is not reported in Table 1.7 as there is only one VIX ETF in that group, which was issued much later than others and traded at a low level with a small size. Considering the data availability and group size affect, it is not reported in column (4), (5), (6); however, it is included in the "inverse group" reported in column (1), (2), (3).

Panel A of Table 1.7 presents the results of the models with VIX ETPs categorized into two groups, namely normal and inverse, which are based on their strategies. The results in Panel A of Table 1.7 are consistent with the hypothesis. The fund flow to the normal (inverse) VIX ETP group has a statistically significantly positive (negative) impact on the VIX index. However, the interaction terms are not significant, which is in contrast to the hypothesis that the effect of the fund flow to the inverse VIX ETP group is more pronounced during market turmoil periods. Other variables retain the same sign as in the aggregate model discussed above (see Table 1.6). The time dummy and the shift in the VIX futures term structure factor have significant positive impacts, while the lagged VIX futures price change imposes a significant negative effect on VIX index change.

Panel B of Table 1.7 presents the results of the models with VIX ETPs categorized into three groups, namely normal-short, normal-mid and inverse-short.[†] In line with the hypothesis, the fund flow to the normal-short (inverse short) group has a statistically significant positive (negative) impact on the daily change of the VIX index. The fund flow to the normal-mid group is no longer significant when the interaction terms, the time dummy and the shift in the VIX futures term structure entered the model. The effects of other variables are consistent with the results featured in Panel A of Table 1.7.

1.7 Conclusion

This study examines the fund flows to the VIX exchange-traded products (ETPs) and focuses on their effects on the underlying volatility index during the period January 2009–December 2015. The empirical findings suggest that investors have more

[†] Due to limited observations, the inverse-mid group is exempt in the sample used to run the models, with results featured in Panel B of Table 1.7.

incentives to take long positions in the VIX ETP groups which apply normal tracking strategies when the equity market is calm. Analogously, when the equity market is highly volatile, investors tend to be long in the VIX ETP groups which apply inverse tracking strategies. These findings provide supportive evidence that market participants expect the VIX index to move in a mean-reverse way (Whaley, 2008; Leung, Li and Wang, 2015).

The important contribution of this chapter is the fact that it provides arguments for the discussion on the implication of the rapid growth of VIX-linked exchange-traded products. Market regulators and financial media are concerned that financial innovations such as VIX ETFs and ETNs may cause instability on the equity and derivatives market during crisis periods. In 2015, the Security and Exchange Commission was concerned how the ETP can affect underlying market (see SEC's File No. S7-11-15 including the Question 17). The results of this study indicate that the fund flows into different VIX ETP groups have statistically significant impacts on the VIX index. More specifically, the fund flow to the normal (inverse) VIX ETP groups has a significant positive (negative) effect on the VIX index. However, in contrast to the expectations formulated by financial press, it is found that the funds flow to VIX ETPs do not have additional statistically significant impacts on the level of the VIX index during high-volatility periods.

Chapter 2

High policy uncertainty and low market volatility – an academic puzzle?

Abstract

Motivated by the extremely low level of the CBOE VIX accompanied by the high level of U.S. economic policy uncertainty in the period of late 2016 to the end of 2017, I examine the factors affecting the relationship between those two realities. This analysis shows that the quality of political/economic signals, the divergence of investors' opinions, and representativeness bias influence the link between the fear gauge and economic policy uncertainty. Specifically, representativeness bias caused by recent low realized volatility weakens the positive relationship between the VIX and policy uncertainty consistently, while the impacts of the quality of political/economic signals and investors' divergence of opinion depend on the overall level of economic policy uncertainty. Given the level of policy uncertainty, the results explain the record-low VIX level post the 2016 presidential election.

Keywords: VIX, Economic Policy Uncertainty, Baker-Bloom-Davis Index, AAII Sentiment Survey, Representativeness Bias, Investors' opinions

JEL codes: G11, G14, G23, G41

2.1 Introduction

The Chicago Board Options Exchange's (CBOE) volatility index (VIX), which is a measure of the implied volatility of S&P 500 index options, has been widely used as a proxy for the "fear gauge" of market participants.[19] Empirical studies have documented a significant positive correlation between stock market volatility and economic policy uncertainty (Li, Balcilar, Gupta, and Chang, 2016; Sum and Fanta, 2012; Liu and Zhang, 2015). Periods characterized by high economic policy uncertainty often experience significantly lower real stock market returns (Kang and Ratti, 2013; Brogaard and Detzel, 2015). Uncertainty over government policy actions raises the volatility of the stochastic discount factor, resulting in higher risk premia and more volatile stock returns (Pastor and Veronesi, 2012). Economic policy uncertainty also swings investors' views on the impact of the current policy and the probability of a policy change (Pastor and Veronesi, 2012), leading to a greater extent of disagreement among market participants. Divergence in investors' opinions, in turn, intensifies stock market volatility. As the VIX is derived from the prices of S&P 500 index options, which tend to be more expensive in a volatile economic policy environment (Kelly, Pastor, and Veronesi, 2016), it is expected that a higher degree of economic policy uncertainty is associated with a higher VIX level.

Since the 2016 U.S. presidential election, the VIX has hovered at extremely low levels, while both economic policy uncertainty, proxied by the widely used Baker-Bloom-Davis (BBD) news-based index, and the S&P 500 index have reached high

[19] Launched in 1993 by the CBOE, the VIX captures investors' expectations of stock market volatility over the next 30-day period. The level of the VIX is important not only for market participants who consider it as a barometer of the equity market volatility, but also for investors of VIX-related products. Crisis periods are characterized by higher values of the VIX, when it is expensive for investors to close losing positions (Whaley, 2000; Whaley, 2008; Shaikh and Padhi, 2015).

levels.[20] The average level of the VIX in 2017 corresponds to the 2nd percentile of its values over the period 1997–2016, while the average of the BBD news-based index in 2017 was equivalent to its 77th percentile measured over the same time period. On 3 November 2017, the VIX plummeted to its lowest closing value of 9.14, whereas the S&P 500 index reached a historical peak of 2587.84 that same day. The substantial divergences between the VIX and the BBD indices have continued for an extended period of time. This puzzling phenomenon is unlikely to be the outcome of a short-lived anomaly. The observed divergences suggest that factors other than the performance of the U.S. equity market may have played important roles in affecting the relationship between the VIX and economic policy uncertainty, driving the VIX to its extremely low levels.

In an effort to find an explanation for the observed puzzle of the low VIX and the high policy uncertainty in 2017, I look beyond the studies which link stock market volatility with economic policy uncertainty. An examination of relevant literature allows me to test three potential explanatory factors, namely, the quality of political signals, investors' diverse opinions, and representativeness bias. I am not aware of any studies which empirically examine the contributions of those three factors to this puzzling phenomenon.

The analysis on the quality of political signals of this study is guided by the theoretical model of Pastor and Veronesi (2013). Pastor and Veronesi formulated the model to examine the asset pricing implications of political uncertainty. One implication of their model is a relationship between the precision of political signals and stocks'

[20] The Baker-Bloom-Davis (BBD) news-based index and the BBD overall index are often employed as proxies for the extent of economic policy uncertainty and have been employed in a number of studies (e.g. Brogaard and Detzel, 2015, Loh and Stulz, 2018). The constructions of the BBD news-based index and BBD overall index will be discussed in the data section.

volatility. In particular, the model claims that political news sends signals which suggest the course of action a government may pursue. Rational investors perceive political signals, dissect relevant information, and update their views on prospective economic policies. In this learning process, investors use the continuous flow of political news to estimate the political cost associated with potential new polices and revise their beliefs about the likelihood of various future government policies. Investors then respond to those political signals, and their responses are seen in share prices. However, when political news is noisier, the learning about the political cost associated with potential new polices will be less efficient. As a consequence, investors tend to be skeptical about governments' prospective policy actions. Investors continue to observe political signals, but they pay less attention than they would otherwise (Pastor and Veronesi, 2017). In other words, in spite of the high economic policy uncertainty, noisy political signals are likely to result in small updates in investors' beliefs, which lead to lower political risk premia and market volatility.[21] This chapter contributes to the literature by empirically testing this implication of Pastor and Veronesi's model.

Another theoretical model constructed by Dumas, Kurshev, and Uppal (2009) indicates that higher opinion divergence could lead to higher market volatility. In their model, one group of investors hold proper opinions about public signals, while the other investors are overconfident. The overconfident investors revise their beliefs too often regarding economic prospects and tend to overreact to new public signals, which leads to volatile stock price movements and higher market volatility. The model suggests that the larger the fluctuations in the sentiment of overconfident investors relative to investors with the proper beliefs, the higher the market volatility. In an environment inundated with

[21] In the study of Pastor and Veronesi (2013), they discussed the impact of the precision of political signs in the theoretical model in section 4.1.2 *Political shocks*.

imprecise public political signals, it is more difficult for investors to interpret conflicting information and form accurate views on prospective policy actions. Investors are more likely to hold different beliefs on the probability and the potential impacts of a policy change (Pastor and Veronesi, 2012, 2013). Higher divergence in investors' opinions tends to result in higher expected market volatility (Banerjee and Kremer, 2010). In this respect, noisy signals create divergences in investors' opinions, which intensify market volatility. In this study, I link belief divergence with policy uncertainty and empirically test the implications of the model by Dumas, Kurshev, and Uppal (2009).

The year 2017 also presented an interesting background to reflect on the low volatility accompanied by the strong performance of the U.S. equity market and its potential impacts on investors' behaviors. According to proponents of behavioral finance, investors exhibit representativeness bias in their trading activities. They expect a price continuation based on past "trends" and perceive investment risks based on their most recent investment experience (De Bondt, 1993). Investors who exhibit representativeness bias tend to believe that the low market volatility with an ongoing bullish spell in the U.S. equity market will continue. Thus, in an environment characterized by continuously low market volatility, investors are likely to overlook political signals and underestimate the impact of economic policy uncertainty on investment risks. The representative bias of investors is likely to contribute to a lower degree of market volatility.

By examining these factors mentioned above, I find that the quality of political signals plays an important role in explaining the level of the VIX. More precisely, I show that policy uncertainty, together with the quality of political signals, helps to explain the level of the VIX. I also find evidence that investors' opinion divergence has a significant impact on expected market volatility and the relationship between policy uncertainty and the VIX. In addition, the results show that the commonly accepted positive relationship between the VIX and economic policy uncertainty is weakened during a time characterized by recently low realized volatility. The reported results provide insights into the dynamics of the co-movement of the VIX and proxies of economic policy uncertainty.

The remainder of this chapter is structured as follows. Section 2 reviews the relevant literature and formulates hypotheses. Section 3 describes the data and variables employed. Section 4 presents the methods. Section 5 discusses the results, and Section 6 concludes with the main findings.

2.2 Literature and Hypothesis

The observed extremely low level of the VIX, albeit with a high degree of economic policy uncertainty, has drawn increasing attention from practitioners and researchers.[22] The year 2017 presented this study with an interesting background to examine three factors, which have received little attention in *empirical* studies on the VIX: the quality of political signals, divergence of investors' opinions and representativeness as one of investors' behavioral biases.

2.2.1 Quality of economic/ political signals

The studies conducted by Pastor and Veronesi (2012, 2013) develop theoretical models and explain the relationships between stock price, market volatility and economic policy uncertainty. In their proposed model, the government decides the economic policies to be adopted, while investors are uncertain about government's prospective policy actions. Changes in economic policies will lead to price reactions in the financial markets, and the magnitudes of the reactions depend on the extent to which the changes

[22] See, for example, Banerji (2017), Figlewski (2017), Ciolli (2017), Moyo (2017), Pastor and Veronesi (2017), Watts (2017) and Weber (2018).

were anticipated. Pastor and Veronesi consider two types of uncertainty: the uncertainty regarding whether a current policy will be changed and the uncertainty regarding the impact of a new policy on share prices and market volatility. They find that both types of uncertainties significantly affect stock price and market volatility. In particular, Pastor and Veronesi (2013) show that stock prices are driven by three types of shocks, namely capital shocks, impact shocks, and political shocks. Capital shocks and impact shocks influence stock prices by affecting the amount of capital and causing investors to revise their beliefs about the impact of the prevailing government policy, respectively. Political shocks, the third type of shocks, are driven by investors' learning about the political cost associated with potential new policies. Specifically, political shocks reflect the continuous flow of political news and lead investors to update their beliefs about the likelihood of the different potential future policy choices. In their model, Pastor and Veronesi document that the effect of political shocks on stock prices and market volatility is greater when political signals are more precise and when there is more policy uncertainty. In other words, the model implies that market volatility is an increasing function of the product of political uncertainty and the quality of political signals (Pastor and Veronesi, 2017). When political signals are precise on governments' prospective policy actions, it is expected that market volatility and economic policy uncertainty move together. However, when faced with poor political signals, investors do not update their beliefs often and hesitate to react in the financial markets. In this situation, it is not unusual to observe low market volatility, albeit with a high level of economic policy uncertainty. This scenario is consistent with the puzzling phenomenon observed in the U.S. in 2017.

In over 12 months following the 2016 presidential election, U.S. investors were bombarded with a large flow of political news. Most frequently heard on media were the appointments and dismissals of high-ranking officials in the White House office and the cabinet, the announcements of economic reforms, and plans to change domestic and foreign policies. The year 2017 was also inundated with a large amount of fake news and half-truths. According to the *Washington Post Fact Checker*'s database, as of 2 March 2018 President Donald J. Trump had made 2,436 false or misleading claims in the 406 days since he took the oath of office.[23] The prevalence of fake news and imprecise news made it difficult for investors to interpret political signals, to dissect reversals and contradictions, and to evaluate their potential impacts on investment risks (Pastor and Veronesi, 2017). As a result, investors tend to wait and see, which leads to lower market volatility. In light of the theoretical model proposed by Pastor and Veronesi (2013) and the political developments in the U.S. in 2017, I put forward the following hypothesis:

(H2-1) Policy uncertainty is an important determinant of market volatility; however, the impact of policy uncertainty is weaker when the precision of political signals is low.

2.2.2. Lack of consensus among investors

Past studies show evidence that investors tend to be overconfident and often overreact to political signals (De Bondt and Thaler, 1985; Darrat, Zhong, and Cheng, 2007). Dumas, Kurshev, and Uppal (2009) formulate a theoretical model to analyze the effects of the difference of opinions on stock price volatility. In their model, a stream of dividends is paid and the fundamental determinant variable of dividends is not observable. All investors are risk averse, allowed to short sell, and receive information in the form of the current dividend and a public signal. Investors have different opinions about the

[23]Source: President Donald J. Trump has made 2,436 false or misleading claims so far https://www.washingtonpost.com/news/fact-checker/wp/2018/03/02/president-trump-made-2436-false-or-misleading-claims-so-far/?utm_term=.d9d7e3542240

correlation between innovations in the signals and innovations in the unobserved variables. Some overconfident investors believe that this correlation is positive, while, in fact, it equals zero. These investors therefore give too much weight to the signals, while the other investors know the true correlation and form “proper” beliefs. Dumas, Kurshev, and Uppal refer to the fluctuations in the expectations of overconfident investors relative to those with the proper beliefs as fluctuations in “sentiment.” Their model shows that the overconfident investors change their beliefs too often about economic prospects. Specifically, when overconfident investors receive a new public signal, they tend to overreact to it, which consequently generates volatile stock price movements and leads to higher market volatility. The model implies that the larger the fluctuations in the sentiment of overconfident investors relative to investors with the proper beliefs, the higher the market volatility.

As Pastor and Veronesi (2012, 2013) argue, in a volatile economic policy environment with potentially more public political signals, investors are more likely to disagree on the potential impacts of policy changes, which results in a higher degree of opinion divergence. The lack of consensus among investors about the future direction of the market is confirmed by close to equally divided opinions among investors. Moreover, considering the large flow of imprecise news released by the U.S. government in 2017, it was even more difficult for investors to interpret low-quality political signals. Thus, the degree of opinion divergence among investors could be higher than ever observed. A number of studies on heterogeneous opinions present strong evidence that divergence in investors’ opinions significantly raises market volatility (Scheinkman and Xiong, 2003; Buraschi and Jiltsov, 2006; Andrei, Carlin, and Hasler, 2015). In light of this discussion, I formulate the second hypothesis:

(H2-2) The effect of policy uncertainty on market volatility is stronger when opinion

divergence more among investors.

2.2.3. Bullish spell and fear gauge

Human beings tend to judge a situation based on their most recent encounters instead of evaluating the situation as it is now (Tversky and Kahneman, 1974), which is the so-called representativeness bias. The fact that people have a relatively short memory further aggregates the implication of the representativeness bias. Similarly, investors are prone to perceive an investment as good or bad based on its most recent performance (De Bondt and Thaler, 1985; Benartzi and Thaler, 1995; Barberis, Shleifer, and Vishny, 1998), and expect that the recent trends in prices will persist (De Bondt, 1993). In other words, investors tend to expect that the recent trends in prices are representative of the future trends, and consequently, they are likely to buy equities that have recently gained in value (Shleifer, 2000; Kim and Nofsinger, 2008). Similarly, investors are likely to expect the recent low level of market volatility will continue and last for a longer period in the future.

Previous studies on behavioral finance have presented supportive evidence that the representativeness bias influences investors' interpretations of market signals and their expectations of market performance. Dhar and Kumar (2001) examined the impacts of price trends on the trading decisions of more than 40,000 householders in the U.S. They observed that investors' buying and selling decisions are affected by short-term price trends. Greenwood and Nagel (2009) investigated the roles of inexperienced investors in the formation of asset price bubbles prior to the global financial crisis (GFC). They reported that inexperienced mutual fund managers exhibited representativeness bias, as evidenced by their investment decisions to increase technology stock holdings during the run-up to the GFC and to decrease these holdings during the downturn. Chernenko, Hanson, and Sunderam (2016) also documented that the representativeness bias significantly influences inexperienced mutual fund managers in their holdings of securitized products. Inexperienced managers tend to view the tranquil years prior to the GFC as representative of future years. As a result, these managers tend to underestimate the risks of a disruption in financial markets and they perceive risky non-traditional securitized products to be more attractive. Outside the U.S., Chiang, Hirshleifer, Qian, and Sherman (2011) examined how the experience in IPO auctions affects investors' decisions to bid in subsequent auctions in Taiwan. They observed that individual investors become optimistic after achieving good investment returns, which is consistent with the representativeness bias documented in behavioral finance literature.

This analysis reveals that the end of December 2017 marked the 14th consecutive month over which the S&P 500 Total Return Index achieved positive returns accompanied by low levels of the VIX and realized market volatility. Since 1871, such persistent positive performance has only occurred six times, with each bullish streak lasting at least for 12 consecutive months. The longest bullish spell of 15 months was recorded in the late 1950s. As the continuously low market volatility and bull market unfolded in 2017, investors were more likely to expect this low volatility level accompanied by the strong performance of the stock market to persist, and therefore they let their guard down. They tended to underestimate potential investment risks and lowered their assessment of market volatility. If a negative economic political signal arrived at such a time, its impact on market volatility was likely to be less pronounced than at other times. Thus, I put forward the third hypothesis:

(H2-3) Representativeness bias of low market volatility weakens the relationship between policy uncertainty and the VIX.

2.3 Data

This study covers a long period from 2 January 1997 to 31 December 2017. The sample includes 5281 daily observations of the VIX, the S&P 500 index, and the BBD news-based and BBD overall indices. The daily closing values of the S&P 500 index, the VIX, and the BBD daily index, the weekly values of the American Association of Individual Investors (AAII) sentiment index, and the monthly values of the BBD news-based and BBD overall indices were collected from Bloomberg.

2.3.1 Variables

2.3.1.1 Economic policy uncertainty

I employ the BBD news-based policy uncertainty index as the proxy for economic policy uncertainty and use the BBD overall policy uncertainty index as an alternative measure in the robustness test.[24]

The BBD news-based policy uncertainty index (*Uncertainty*) quantifies the coverage of policy-related economic uncertainty in 10 popular newspapers, namely *USA Today*, the *Miami Herald*, the *Chicago Tribune*, the *Washington Post*, the *Los Angeles Times*, the *Boston Globe*, the *San Francisco Chronicle*, the *Dallas Morning News*, the *Houston Chronicle*, and the *Wall Street Journal*. To construct the BBD news-based uncertainty index, the terms related to economic and policy uncertainty were searched in each newspaper and each month from January 1985. To meet the criteria for being counted, each policy uncertainty article had to include the terms in all three categories pertaining to uncertainty, economy, and policy.[25] The monthly count of policy uncertainty articles in each newspaper was divided by the respective monthly total number of articles. The

[24] Source: http://www.policyuncertainty.com/us_monthly.html

[25] The terms searched in each article include uncertainty or uncertain, economic or economy, and one or more of the following terms: congress, legislation, white house, regulation, federal reserve, deficit.

resulting monthly series for each newspaper was then normalized to have a unit standard deviation before being summed across newspapers to obtain a monthly multi-paper index. This index was then re-normalized to an average value of 100. [26]

The BBD overall index (*OverallBBD*) consists of three components. The first component is the BBD news-based policy uncertainty index, as discussed above. The second component reflects the number of federal tax code provisions set to expire in future years. The third component captures the degree of disagreement among economic forecasters. To construct the BBD overall index, each component was first normalized by its own standard deviation over the periods. The BBD news-based uncertainty index accounts for a half of the BBD overall index, while each of the other three measures (the tax expiration index, the CPI forecast disagreement measure, and the federal/ state/ local purchases disagreement measure) accounts for a sixth.

Figure 2.1 depicts the time-varying relationship between the VIX, the BBD news-based index, and the BBD overall index. Panel A of Figure 2.1 features the time-varying ratios of each BBD index to the VIX over the period 1997–2017. Both ratios jumped to the highest values shortly after the U.S. presidential election in November 2016, and since then they have gone up more than double.

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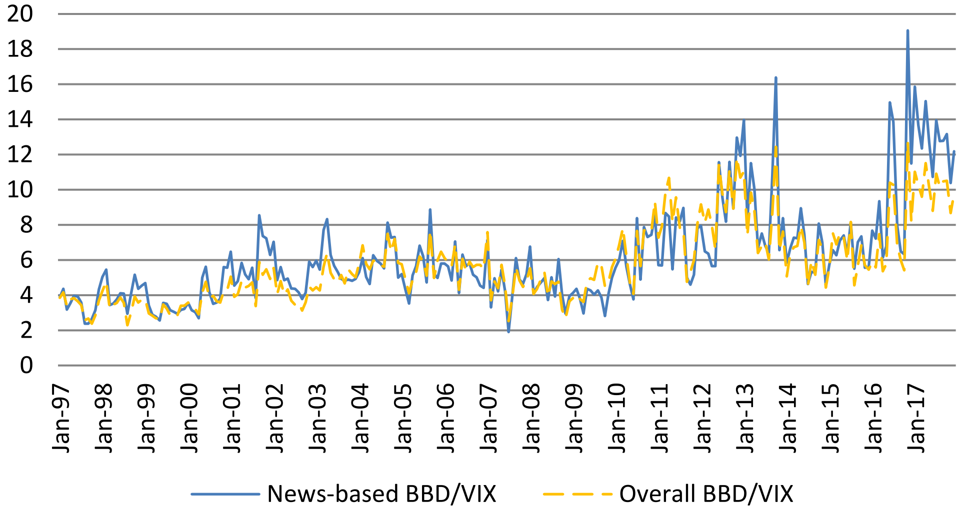
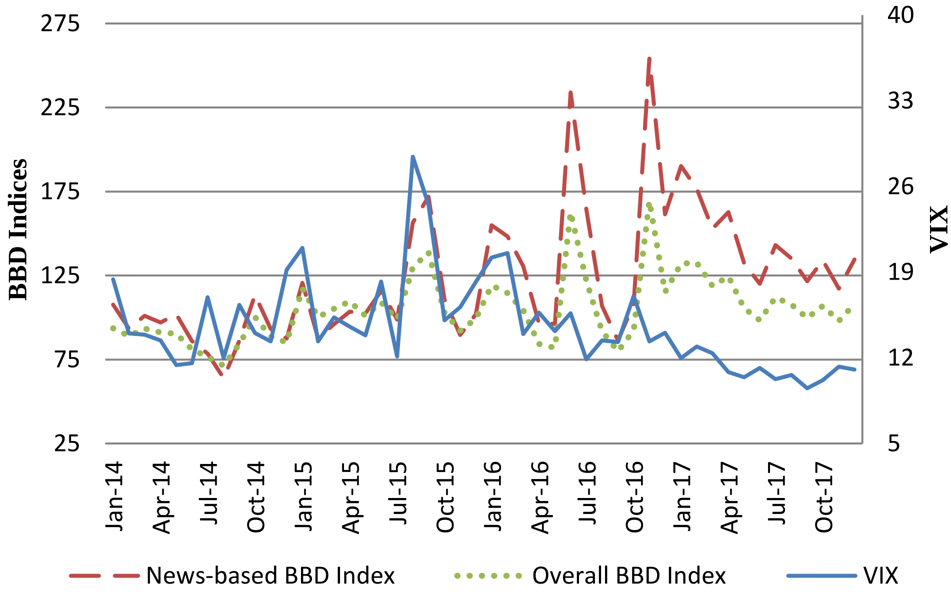
[26] Monthly BBD indices have been widely applied as the proxy for economic policy uncertainly in the literature (see, for example, Klößner and Sekkel, 2014, Liu and Zhang, 2015, Gulen, and Ion, 2015, Bonaime, Gulen, and Ion, 2018).

Figure 2. 1 VIX and Economic Policy Uncertainty

Panel A
Ratio of Uncertainty Indices to VIX



Panel B
Co-movement of VIX and Uncertainty Indices



Panel A presents the ratio of economic policy uncertainty indices (news-based Baker-Bloom-Davis index and overall Baker-Bloom-Davis index) to the VIX from January 1997 to December 2017. Panel B presents the value of the VIX and economic policy uncertainty indices from January 2014 to December 2017

Panel B of Figure 2.1 shows the time series of the VIX, the BBD news-based index, and the BBD overall index during the period 2014–2017. A striking feature in Panel B is the substantial divergence between the VIX and the two BBD indices from April 2016 onwards. The VIX has hovered at historically low levels, whereas the two BBD indices reached their peaks after the U.S. presidential election had concluded.

Table 2.1 reports the average value of the VIX, the news-based BBD index, the overall BBD index, and the S&P 500 index based on the deciles of the VIX over the period 1997–2016. The co-movements between the VIX and the BBD indices were noticeable for the lowest and the highest deciles. For example, the deciles of high values of the VIX correspond to the high values of the BBD indices. The last two columns in Table 2.1 report the 2017 mean value of each index and the 2017 mean as the equivalent percentile of the 1997–2016 values. The average level of the VIX in 2017 corresponds to the 2nd percentile over the period 1997–2016, while the average of the BBD news-based index in 2007 is equivalent to the 77th percentile of its values measured over 1997–2016. The mean value of the S&P 500 index in 2017 was the highest of its values over the period 1997–2017. This puzzling phenomenon motivates me to conduct a thorough analysis of the dynamics of the VIX and policy uncertainty.

Table 2. 1 CBOE VIX, Economic Policy Uncertainty, and S&P 500 Index

VIX deciles (1997-2016)	1-10th	11-20th	21-30th	31-40th	41-50th	51-60th	61-70th	71-80th	81-90th	91-100th	2017	Means of 2017 as percentile of 1997-2016
CBOE VIX	11.65	13.26	14.81	16.69	18.66	20.43	22.28	24.49	27.89	39.37	11.09024	2th
News based BBD	79.12	105.70	106.96	112.22	112.06	105.32	110.32	116.55	128.33	170.33	142.6863	77th
Overall BBD	78.28	96.63	103.57	115.88	112.18	101.98	105.17	110.53	114.78	148.99	111.6307	64th
S&P500	1519.60	1668.40	1575.91	1430.03	1273.45	1214.08	1258.01	1233.58	1188.81	977.46	2449.076	Highest value
Observations	504	504	503	501	504	503	503	503	503	503	251	

This table presents the means of the CBOE VIX, news-based Baker-Bloom-Davis (BBD) uncertainty index, overall BBD uncertainty index, and S&P500 index based on the deciles of the VIX for the period 1997–2016. The last two columns present the mean of these indices in 2017 as well as the corresponding percentiles over 1997–2016.

2.3.1.2 The quality of political signals

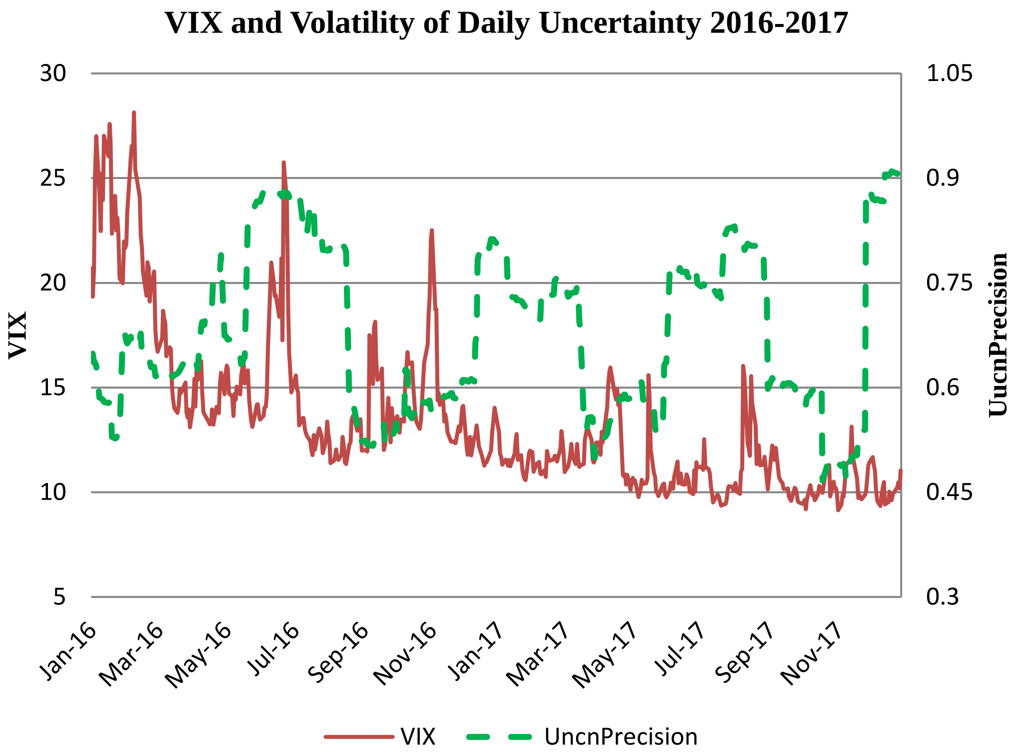
To find the proxy for the precision of political signals, Pastor and Veronesi (2017) suggest using the *Washington Post Fact Checker* data. However, the relatively short history of this dataset makes it unsuitable for this analysis. I propose and compute the three-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision*) as a proxy for the quality of political signals.[27]

A high volatility reflects the prevalence of imprecise political signals. For robustness tests, I compute the two-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision_2m)* as an alternative precision measure.

Figure 2.2 depicts the time series of the VIX and the three-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision)*. A striking feature in Figure 2.2 is the substantial divergence between the two series following the 2016 U.S. presidential election. The VIX plummeted to extremely low levels, while *Imprecision* experienced three spells of substantial high values.

27 Source: http://www.policyuncertainty.com/us_daily.html

Figure 2. 2 Precision of Political Signals and the CBOE VIX



This figure presents the value of the VIX and the quality of policy uncertainty (*Imprecision*), measured by the volatility of the daily percentage changes of the BBD news-based daily index within a three-month rolling period from January 2016 to December 2017.

2.3.1.3 Divergence in investors' opinions

To capture investors' opinion divergence, I employ two measures calculated with the data of the American Association of Individual Investors (AAII) Sentiment Survey. AAII has conducted weekly surveys since 1987. In each survey, its members are asked a simple question: Do you feel the direction of the stock market over the next six months will be up (*bullish*), no change (*neutral*), or down (*bearish*)? The AAII Sentiment Survey is conducted each week, and is open to all AAII members.[28] The results of the survey are automatically tabulated in the AAII database and published online early every Thursday morning. The survey results are circulated by various organizations and media outlets, including Barron's and Bloomberg.

The measure for investors' opinion divergence, *Dispersion*, is calculated as the difference between the highest and lowest AAII spot sentiment percentages (bullish, bearish, and neutral).[29] When investors' opinions disagreement is low, expectation of future market movement should be aligned among market participants. In such a case, most investors agree on the expected direction which the market will move towards. As a consequence, there will be a dominant sentiment among market participants. The dominant sentiment could be either bullish, bearish, or neutral, whose percentage will be much higher than those of the subdominant sentiments, and will lead to a relatively high deviation between the highest and lowest sentiment percentages. Therefore, a higher deviation between the highest and lowest sentiment percentages (*Dispersion*) indicates a lower level of investors' disagreement. On the other hand, when the disagreement among

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[28] AAII has more than 160,000 members. A typical AAII member is a male in his mid-60s, who has obtained either a bachelor or a post-graduate degree. AAII members tend to be affluent, with a median investment portfolio size of over US$1 million. They possess moderate investment knowledge and engage primarily in fundamental analysis.

[29] For example, at a time when the bullish sentiment percentage is 40, the neutral sentiment percentage is 25, the bearish sentiment percentage is 35, *Dispersion* equals to 15, which is calculated as the difference between the highest sentiment percentage (40 for bullish) and lowest sentiment percentage (25 for neutral).

market participants is high, investors are more likely to stick with their own opinions about the market's future movement and the sentiment percentages tend to be closer to each other. For instance, in the scenario when opinion divergence among market participants is extremely high, the sentiment percentages of bullish, bearish, and neutral would be the same, which will make the deviation between sentiment percentages (*Dispersion*) equal to zero. Therefore, a smaller difference between the highest and lowest sentiment percentages (*Dispersion*) indicates a higher level of investors' opinion divergence.

As a robustness test, I employ an alternative measure to account for the degree of divergence in investors' opinions, *Dispersion_SD*, which is defined as the standard deviation of AAII sentiment percentages (bullish, bearish, and neutral).[30] A high value of *Dispersion_SD* indicates that the deviation between sentiment percentages is high, and hence there is a dominant sentiment and consensus among market participants, suggesting investors' opinion divergence is low.

2.3.1.4 Representativeness bias

To test how investors' representativeness bias affects the relationship between policy uncertainty and the VIX, I applied a measure of representativeness bias constructed using realized and implied market volatility. In first step, we calculate the inverse of the absolute difference between implied volatility and realized volatility for the same period of one month:

[30] For example, at a time when the bullish sentiment percentage is 40, the neutral sentiment percentage is 25, the bearish sentiment percentage is 35, *Dispersion_SD* is calculated as the standard deviation of the three sentiment percentages (40, 25, 30) and equals to 7.64.

$$R\_I = \frac{1}{|Realised\ volatiltiy_t - VIX_{t-22}|}\ ,$$

where $Realised\ volatiltiy_t$ is the one-month realized volatility of S&P 500 index estimated at time t; VIX_{t-22} is the VIX value one month before. The smaller is the difference in the denominator of the above fraction, the higher is a predictive power of implied volatility in one-month window. Consequently, a higher value of R_I indicating a higher likelihood that the investors are likely to be affected by representativeness bias. Because representativeness bias influences market participants during calm periods (when the VIX is low) and during market downturn period (when the VIX is high), the R_I needs an adjustment. Therefore, we multiple *R_I* with dummies to distinguish these effects for crisis and non-crisis periods. More specifically, we first create a dummy, *VIX_low,* which is set to one if the VIX is below its sample mean, and zero otherwise. Next, we create another dummy, *VIX_high*, which equals one if the VIX is above its sample mean, and zero otherwise. Then we multiple *R_I* by *VIX_low* and *VIX_high*, respectively, and get two variables, namely *RI_low* and *RI_high*. Hence, the construction of *RI_low (RI_high)* allows to make distinction between representativeness bias among investors occurring in low-VIX (high-VIX) environment. [31] A higher value of *RI_low* suggests greater probability for representativeness bias. If investors affected by representativeness bias are likely to expect the current low level of market volatility will persist for a longer period. Consequently, they underestimate potential investment risks associated with policy uncertainty and lowered their assessment of market volatility.

[31] The approach of distinguishing the effects by high-VIX and low-VIX periods shares similar idea with that of Bessembinder, Chan and Seguin (1996), who distinguished the effects of the increase and decrease of futures' open interest.

As robustness tests, I consider alternative measures for low-volatility time periods and create a set to one if the latest one-month realized volatility is lower than the average monthly volatility in last 12 months.

2.3.2 Statistics

The descriptive statistics of the variables employed in this study are summarized in Table 2.2. Over the study period 1997–2017, the VIX varied between 9.14 and 80.86, with a mean value of 20.48. Additional analysis (not reported) shows that the 5th percentile of the VIX was 11.18. Of the daily observations in the left tail (low market volatility), there were 31 found in 2005, 50 in 2006, 28 in 2007, 11 in 2014, and 146 in 2017. The 95th percentile of the VIX was 35.81. Of the observations in the right tail (high market volatility), 8 were found in 1997, 30 in 1998, 7 in 2001, 40 in 2002, 67 in 2008, 80 in 2009, 5 in 2010, 28 in 2011, and 2 in 2015.

The daily returns of the S&P 500 index over the study period varied between -9% and 11.6%; both extreme values were observed in October 2008. The mean of daily returns for the main U.S. market benchmark is close to zero. The logarithm value of the latest annualized one-month realized volatility, *Realized Volatility,* has a mean of 2.68, and ranged between 1.24 and 4.46.

In regard to the measures of the quality of political signals, the average of the three-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision*) is 0.92, while the average of the two-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision_2m*) is 0.90. *Imprecision* ranged between 0.33 and 3.57 while *Imprecision_2m* ranged between 0.3 and 4.26.

With regards to economic policy uncertainty, the monthly BBD news-based index

(*Uncertainty*) ranged between 44.87 and 283.67, with a mean value of 115.99. The monthly BBD overall index (*OverallBBD*) varied between 57.20 and 245.13, with an average of 108.94.

In terms of investors' opinion divergence, the mean of the difference between the highest and lowest AAII spot sentiment percentages (*Dispersion*) is 0.214 while the average value of the standard deviation of AAII spot sentiment percentages (*Dispersion_SD*) is 0.113. *Dispersion* ranged between 0.008 and 0.633, and *Dispersion_SD* varied between 0.005 and 0.361. On average, about 40% of AAII members are bullish, 30% are bearish and 30% are neutral about the prospects of the financial market. The highest percentage of bullish AAII members reached 75% in January 2000. With regards to the dummies capturing low-volatility environments (representativeness bias), *LV* has a mean of 0.59 and *LV_2m* has a mean of 0.58.

The correlation matrix for the key independent variables is presented in Table 2.3.[32] As shown in the table, except the correlation between *realized volatility* and *LV* dummy, the other independent variables are not highly correlated with one another. As *realized volatility* and *LV* are not simultaneously included in any of the regression estimate the set of the independent variables are unlikely to raise any multicollinearity issues.

[32] In Table 2.3, I only present the correlation matrix for a set of main independent variables for reasons of brevity. The correlation matrix for all variables used in robustness tests shows consistent results and is available upon request.

Table 2. 2 Summary Statistics

Variables	Obs	Mean	Standard Deviation	Min	Max
VIX	5281	20.479	8.449	9.140	80.86
ΔS&P500	5281	0.000	0.012	-0.090	0.116
S&P500	5281	1387.2	421.6	676.5	2690.2
Uncertainty	5281	116.02	44.84	44.78	283.67
Realized Volatility	5281	2.678	0.495	1.245	4.458
OverallBBD	5281	108.94	35.62	57.20	245.13
Imprecision	5281	0.920	0.545	0.327	3.574
Imprecision_2m	5281	0.903	0.575	0.305	4.264
Dispersion	5281	0.214	0.112	0.008	0.633
Dispersion_SD	5281	0.355	0.042	0.238	0.476
LV	5281	0.593	0.491	0.000	1.000
RI_low	5281	0.352	3.099	0.000	131.7
RI_high	5281	0.302	2.740	0.000	119.2
AAII_Bullish	5281	0.398	0.100	0.165	0.750
AAII_Bearish	5281	0.307	0.098	0.067	0.703
AAII_Neutral	5281	0.295	0.081	0.077	0.529

This table presents the summary statistics for all variables examined in the study as well as relevant market indices used for calculation. *VIX* is the value of the CBOE Volatility index. *S&P500* is the value of equity market index. *ΔS&P500* is the daily log return of the S&P 500 index. *Realized Volatility* is the log value of the annualized volatility of S&P 500 daily returns within a rolling one-month time period. *Uncertainty* is the value of the Baker, Bloom and Davis (BBD) news-based policy uncertainty index. *OverallBBD* is the value of the BBD overall policy uncertainty index. *Imprecision* is the measure on the quality of political signals, calculated as the three-month rolling volatility of the daily returns of the BBD daily index. $Imprecision\_2m_t$ is the alternative measure on the quality of political signals, which is calculated as the two-month rolling volatility of the daily returns of the BBD daily index *Dispersion* is the measure of investors' opinion divergence, defined as the difference between the highest AAII sentiment percentage and the lowest AAII sentiment percentage. *Dispersion_SD* is the alternative measure of investors' opinion divergence, calculated as the adjusted standard deviation of the AAII bullish percentage, AAII bearish percentage, and AAII neutral percentage. *LV* is a dummy to capture representativeness bias, which is set to one if the latest one-month realized volatility is lower than the average monthly volatility in last 12 months. *RI_low* is calculated as $1/|\ Realized\ volatility_t - VIX_{t-22}\ |$ if the VIX is lower than its sample mean, otherwise zero. *AAII_Bullish* is the reported bullish percentage in the AAII index. *AAII_Bearish* is the reported bearish percentage in the AAII index. *AAII_Neutral* is the neutral percentage in the AAII index.

Table 2. 3 Correlation Matrix for Independent Variables

	ΔS&P500	Realized Volatility	Uncertainty	Imprecision	Dispersion
Realized Volatility	-0.004				
Uncertainty	-0.030**	0.321***			
Imprecision	-0.004	0.047***	-0.253***		
Dispersion	-0.010	0.117***	-0.120***	0.022	
RI_low	0.004	-0.022*	-0.024**	0.014	-0.027**

This table presents the correlation matrix for the key variables. *VIX* is the log value of VIX. *ΔS&P500* is the daily log return of equity market index. *Realized Volatility* is the log value of the annualized volatility of S&P 500 daily returns within a rolling one-month time period. *Uncertainty* is the value of the BBD news-based uncertainty index. *Imprecision* is the measure for the quality of political signals, which is calculated as the three-month rolling volatility of the daily returns of the BBD daily index. *RI_low* is calculated as 1/| $Realized\ volatility_t$ – VIX_{t-22} |. *Dispersion* is the measure for investors' opinion divergence, calculated as the difference between the highest AAII sentiment percentage and the lowest AAII sentiment percentage. if the VIX is lower than its sample mean, otherwise zero. *,**,*** corresponds to statistical significance at the 10%, 5%, and 1% level, respectively.

2.4 Methodology

In order to test hypothesis (H2-1) regarding policy uncertainty and the quality of political signals, the following model was estimated:

$$VIX_t = \lambda_0 + \lambda_1 \Delta S\&P500_t + \lambda_2 Trend_t + \lambda_3 RealizedVolatility_t + \lambda_4 Uncertainty_t$$
$$+\lambda_5 Imprecision_t + \lambda_6 Uncertainty_t \cdot Imprecision_t + \varepsilon_t \quad (2.1)$$

where

VIX_t is the logarithm of the VIX value at time t.

$\Delta S\&P500_t$ is the daily log return of S&P 500 index at time t.

$Realized\ Volatility_t$ is the logarithm of the annualized volatility of S&P500 daily returns for a rolling one-month time period.

$Uncertainty_t$ is the measure for the degree of economic policy uncertainty at time t proxied by the monthly BBD news-based index.

$Imprecision_t$ is the measure of the quality of political signals, which is calculated as the three-month rolling volatility of the daily percentage changes of the BBD daily index.

$Trend_t$ is the time trend variable which controls for potentially omitted trending variables.

To test hypothesis (H2-2) about investors' opinion divergence, the following model was estimated:

$$VIX_t = \lambda_0 + \lambda_1 \Delta S\&P500_t + \lambda_2 Trend_t + \lambda_3 RealizedVolatility_t + \lambda_4 Uncertainty_t$$
$$+\lambda_5 Dispersion_t + \lambda_6 Uncertainty_t \cdot Dispersionn_t + \lambda_7 Imprecision_t$$
$$+\lambda_8 Uncertainty_t \cdot Imprecision_t + \varepsilon_t \quad (2.2)$$

where $Dispersion_t$ is the measure for disagreements among market participants, and defined as the difference between the highest and the lowest AAII sentiment percentages. Other independent variables are the same as in model (2.1).

To test hypothesis (H2-3) about representative bias, I consider a measure which captures the level of the recent market volatility. If investors have representativeness bias, they are likely to expect the VIX would follow the recent historical pattern. Considering *Realized Volatility* applied in model (2.1) and (2.2) is already a measure of the past volatility, I replace *Realized Volatility* with a dummy which captures the environment of recent historical volatility. I add an interaction term between this dummy and policy uncertainty. By doing this, I examine how representativeness bias affects the relationship between policy uncertainty and the VIX by testing the effect of that interaction term. The following model was estimated:

$$\begin{aligned} VIX_t = {} & \lambda_0 + \lambda_1 \Delta S\&P500_t + \lambda_2 Trend_t + \lambda_3 Uncertainty_t + \lambda_4 RI\_low_t \\ & + \lambda_5 RI\_low_t \cdot Uncertainty_t + \lambda_6 RI\_high_t + \lambda_7 RI\_high_t \cdot Uncertainty_t \\ & + \lambda_8 Imprecision_t + \lambda_9 Uncertainty_t \cdot Imprecision_t + \lambda_{10} Dispersion_t \\ & + \lambda_{11} Uncertainty_t \cdot Dispersion_t + \varepsilon_t \end{aligned} \tag{2.3}$$

, where *RI_low* is calculated as 1/| $Realized\ volatility_t - VIX_{t-22}$ | if the VIX is lower than its sample mean, otherwise zero; *RI_high* is calculated as 1/| $Realized\ volatility_t - VIX_{t-22}$ | if the VIX is higher than its sample mean, otherwise zero;. Other independent variables are the same as in model (2.2). [33]

2.5 Empirical Results

2.5.1 Precision of political signals

[33] I run augmented Dickey-Fuller tests for the VIX and all the independent variables (except the time trend). The results indicate these variables are stationary.

In this section, I examine the three hypotheses formulated in section 2 of the chapter. First, I examine the effects of policy uncertainty and political signals' quality on the VIX level. Table 2.4 shows the regression estimate of model (2.1), with policy uncertainty proxied by the BBD news-based index (*Uncertainty*). I apply the three-month rolling volatility of the daily returns of the BBD daily index as the measure on the quality of political signals. In all specifications, the parameter estimation is reported with Newey-West standard errors.

Table 2. 4
The Impact of the Quality of Political Signals and Policy Uncertainty on the VIX

	(1)	(2)	(3)
ΔS&P500$_t$	-3.0984***	-3.1071***	-3.1034***
	(0.000)	(0.000)	(0.000)
Realized Volatility$_t$	0.5411***	0.5382***	0.5343***
	(0.000)	(0.000)	(0.000)
Trend $_t$	-0.0001***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)
Uncertainty$_t$	0.0016***	0.0015***	0.0011***
	(0.000)	(0.000)	(0.000)
Imprecision$_t$		-0.0333***	-0.1021***
		(0.000)	(0.000)
Uncertainty$_t$ * Imprecision$_t$			0.0005**
			(0.014)
Intercept	1.5752***	1.6436***	1.7250***
	(0.000)	(0.000)	(0.000)
Adj.R-squared	0.8154	0.8173	0.8180
N	5281	5281	5281

This table presents the results on how policy uncertainty and the quality of political signals can affect the VIX level. The dependent variable is the log value of the VIX at time *t*. *ΔS&P500$_t$* is the daily log return of equity market index. *Trend $_t$* is the time trend control variable. *Realized Volatility$_t$* is the log value of the annualized volatility of S&P 500 daily returns within a rolling one-month time period. *Uncertainty$_t$* is the value of the BBD news-based uncertainty index at time *t*. *Imprecision$_t$* is the measure for the quality of political signals, which is calculated as the three-month rolling volatility of the daily returns of the BBD daily index. Newey-West p-values are reported in parentheses. *,**,*** corresponds to statistically significance at the 10%, 5%, and 1% level, respectively.

The results in Table 2.4 indicate that the BBD news-based index (*Uncertainty*) has statistically significant and positive impacts on the VIX, suggesting that the overall VIX tends to be higher in an environment where policy uncertainty is high. The analysis of specification (2) and (3) reveals that the three-month rolling volatility of the daily returns of the BBD daily index ($Imprecision_t$), has a significantly negative impact on the VIX. On the other hand, the interaction term between policy uncertainty (*Uncertainty*) and the quality of political signals (*Imprecision*) in specification (3) presents a significantly positive sign, which could weaken or even reverse the negative effects of *Imprecision* on the VIX level. This suggests that the sign of the combined impacts of political signals' quality and its interaction term depends on the magnitude of policy uncertainty (*Uncertainty*).[34] These findings are in line with the model presented by Pastor and Veronesi (2012, 2013) that implies VIX is affected by the quality of political signals together with policy uncertainty.

In terms of the fundamental variables, it can be found in Table 2.4 that the coefficient for the daily return of S&P 500 index (*ΔS&P500*) is significantly negative, which indicates higher returns of the equity market index reduces the log level of the fear gauge. The log value of realized volatility is found to be statistically significant and positive, which indicates that higher recent realized volatility increases the VIX.

2.5.2 Investors' opinion divergence

To test hypothesis (H2-2), I next examine the impacts of investors' opinion divergence on the relationship between the VIX and economic uncertainty. The results

[34] Although the magnitude of the interaction term's coefficient is much smaller, it is worth noticing that the mean of Uncertainty is around 116 (see in Table 2.2). The test on the sign of the combined effect of the quality of political signals (*Imprecision*) by policy uncertainty levels is in section 2.5.4.

are presented in Table 2.5. Specification (1) and (2) include the variable measuring opinion divergence, as well as an interaction term between opinion divergence measure and policy uncertainty. Specification (3) further adds the measure of the precision of political signals tested in model (2.1) discussed above (see model (2.2)). In Table 2.5, investors' opinion divergence is proxied by *Dispersion,* which is defined as the difference between the highest and the lowest AAII sentiment percentages. Recall that a high value of *Dispersion* indicates a dominate market sentiment, and therefore low opinion divergence among investors. As shown in Table 2.5, the coefficients of *Dispersion* in specification (2) and (3) are significant and negative, indicating that a low level of opinion divergence among investors (proxied by high values in *Dispersion*) tends to lower the level of the VIX. On the other hand, the coefficients for the interaction terms between policy uncertainty (*Uncertainty*) and opinion divergence (*Dispersion*) in specification (3) is found to be significantly positive, which suggests that the sign of the combined impacts of opinions disagreement and its interaction with policy uncertainty on the VIX could vary with the level of policy uncertainty (*Uncertainty*).[35] These findings indicate that the VIX is affected by investors' opinion divergence together with policy uncertainty.

The findings on policy uncertainty and the quality of political signals are consistent with those reported in Table 2.4 that the policy uncertainty (*Uncertainty*) overall has positive impacts on the VIX level, while the impacts of the quality of political signals (*Imprecision*) with its interaction depend on the level of policy uncertainty.

[35] The test on the sign of the combined effect of opinions dispersion (*Dispersion*) by policy uncertainty levels is provided in section 2.5.4.

Table 2. 5
The Impact of Investors' Opinion divergence and Policy Uncertainty on the VIX

	(1)	(2)	(3)
$\Delta S\&P500_t$	-3.0968***	-3.0539***	-3.0646***
	(0.000)	(0.000)	(0.000)
Realized Volatility$_t$	0.5410***	0.5386***	0.5322***
	(0.000)	(0.000)	(0.000)
Trend $_t$	-0.0001***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)
Uncertainty$_t$	0.0016***	0.0012***	0.0007***
	(0.000)	(0.000)	(0.000)
Dispersion$_t$	0.0170	-0.2019**	-0.2016**
	(0.624)	(0.033)	(0.000)
Uncertainty$_t$ * Dispersion$_t$		0.0019**	0.0017**
		(0.016)	(0.027)
Imprecision$_t$			-0.1020***
			(0.000)
Uncertainty$_t$ * Imprecision$_t$			0.0005**
			(0.012)
Intercept	1.5698***	1.6229***	1.7731***
	(0.000)	(0.000)	(0.000)
Adj.R-squared	0.8153	0.8159	0.8185
N	5281	5281	5281

This table presents the results of the regressions that incorporate the impacts of representativeness bias. The dependent variable is the log value of the VIX at time *t*. *$\Delta S\&P500_t$* is the daily log return of equity market index. *Trend $_t$* is the time trend control variable. *Realized Volatility$_t$* is the log value of the annualized volatility of S&P 500 daily returns within a rolling one-month time period. *Uncertainty$_t$* is the value of the BBD news-based uncertainty index at time *t*. *Imprecision$_t$* is the measure for the quality of political signals, which is calculated as the three-month rolling volatility of the daily returns of the BBD daily index. *Dispersion$_t$* is the measure for investors' opinion divergence, calculated as the difference between the highest AAII sentiment percentage and the lowest AAII sentiment percentage. Newey-West p-values are reported in parentheses. *,**,*** corresponds to statistically significance at the 10%, 5%, and 1% level, respectively.

2.5.3 Representativeness bias

To test how investors' representativeness bias affects the relationship between policy uncertainty and market volatility, I applied a set measure of representativeness bias constructed using realized and implied market volatility, namely *RI_low* and *RI_high*. As discussed before, R*I_low (RI_high)* allows to make distinction between representativeness bias among investors occurring in low-VIX (high-VIX) environment. [36] A higher value of *RI_low* suggests greater probability for representativeness bias.

The results of this scrutiny allow me to test hypothesis (H2-3). Different from previous models, in Table 2.6, I replace the log value of realized volatility with *RI_low* and *RI_high*. I then add their interaction with policy uncertainty (*Uncertainty*) in specification (2) and finally include the measures of the quality of political signals, and opinion divergence in specification (3).

As shown in Table 2.6, *RI_low* and its interaction term are found statistically significant to influence the level of the VIX specification (2) and (3). This finding indicates that representativeness bias in a low-VIX environment affects the relationship between economic policy uncertainty and the VIX. However, when its interaction shows opposite sign with the *RI_low*, which again suggests that the sign of the combined impacts of representativeness bias in a low-VIX environment and its interaction with policy uncertainty on the VIX could vary with the level of policy uncertainty (*Uncertainty*). On the other hand, *RI_high* and its interaction term are insignificant, which suggests that representativeness bias is less likely to play a role in impacting the link between economic policy uncertainty and the VIX when the market

[36] The approach of distinguishing the effects by high-VIX and low-VIX periods shares similar idea with that of Bessembinder, Chan and Seguin (1996), who distinguished the effects of the increase and decrease of futures' open interest.

volatility is high. The results on the quality of political signals are in line with those reported in Table 2.4 and Table 2.5 and the findings on investors' opinion divergence are also consistent with those in Table 2.5.

Table 2. 6
The Impact of Representativeness Bias and Policy Uncertainty on the VIX

	(1)	(2)	(3)
$\Delta S\&P500_t$	-2.7618***	-2.7644***	-2.6310***
	(0.000)	(0.000)	(0.000)
$Trend_t$	-0.0001***	-0.0001***	-0.0002***
	(0.000)	(0.000)	(0.000)
$Uncertainty_t$	0.0044***	0.0045***	0.0012***
	(0.000)	(0.000)	(0.002)
RI_low	-0.0031**	0.0072***	0.0062***
	(0.018)	(0.000)	(0.000)
RI_low*Uncertainty		-0.0001***	-0.0001***
		(0.000)	(0.000)
RI_high	0.0068***	0.0047	0.0100
	(0.004)	(0.694)	(0.436)
RI_high*Uncertainty		0.0000	-0.0000
		(0.853)	(0.753)
$Imprecision_t$			-0.3434***
			(0.000)
$Uncertainty_t$ * $Imprecision_t$			0.0022***
			(0.000)
$Dispersion_t$			-0.7059***
			(0.000)
$Uncertainty_t$ * $Dispersion_t$			0.0063***
			(0.000)
Intercept	3.0523***	3.0492***	3.5846***
	(0.000)	(0.000)	(0.000)
Adj.R-squared	0.4586	0.4593	0.4871
N	5281	5281	5281

This table presents the results of the regressions that incorporate the impacts of representativeness bias. The dependent variable is the log value of the VIX at time *t*. $\Delta S\&P500_t$ is the daily log return of equity market index. $Trend_t$ is the time trend control variable. *Realized* $Volatility_t$ is the log value of the annualized volatility of S&P 500 daily returns within a rolling one-month time period. $Uncertainty_t$ is the value of the BBD news-based uncertainty index at time *t*. $Imprecision_t$ is the measure for the quality of political signals, which is calculated as the three-month rolling volatility of the daily returns of the BBD daily index. $Dispersion_t$ is the measure for investors' opinion divergence, calculated as the difference between the highest AAII sentiment percentage and the lowest AAII sentiment percentage. *RI_low* is calculated as 1/| *Realized* $volatility_t - VIX_{t-22}$ | if the VIX is lower than its sample mean, otherwise zero; *RI_high* is calculated as 1/| *Realized* $volatility_t - VIX_{t-22}$ | if the VIX is higher than its sample mean, otherwise zero. Newey-West p-values are reported in parentheses. *,**,*** corresponds to statistically significance at the 10%, 5%, and 1% level, respectively.

2.5.4 Effect of the interaction terms

As discussed in the previous sections, the coefficient sign for *Imprecision* is found to be different from that of its interaction term with policy uncertainty, while both of the coefficients are significant. This result suggests that the direction of the combined effects of political signals' quality (*Imprecision*) could vary with the level of policy uncertainty (*Uncertainty*). In order to better understand the impact of the quality of political signals (*Imprecision*) and policy uncertainty on the VIX, I estimate the interacted effects of policy uncertainty conditionally on three different levels of the quality of political signals (*Imprecision*), namely the low, average, and high levels. The low level of *Imprecision* is calculated as its mean minus the standard deviation (0.38), while the high level is calculated as the mean plus the standard deviation (1.47). Using results reported in specification (3) of Table 2.6, which includes all the three examined factors, I prepare Figure 2.3. It presents the effects of policy uncertainty (*Uncertainty*) on dependent variable (logarithm of VIX) conditionally on the low, average, and high levels of *Imprecision*.[37] I denote the median level of policy uncertainty (*Uncertainty*) over 1997–2016 as well as the median level in 2017. *Uncertainty* has a median value of 103.8 over 1997–2016, while its median in 2017 is 134.5. As shown in Figure 2.3, the effect of *Uncertainty* on the dependent variable is found to be positive for all three levels of *Imprecision.* Given the median levels of *Uncertainty* over 1997–2016 and in 2017, it can be found that the VIX tends to be lower when *Imprecision* is high, which is consistent with Pastor and Veronesi (2012, 2013) suggesting that the imprecision of political signals decreases market volatility. However, it can also be noticed that the effect is reversed when the level of policy uncertainty (*Uncertainty*) moves beyond a

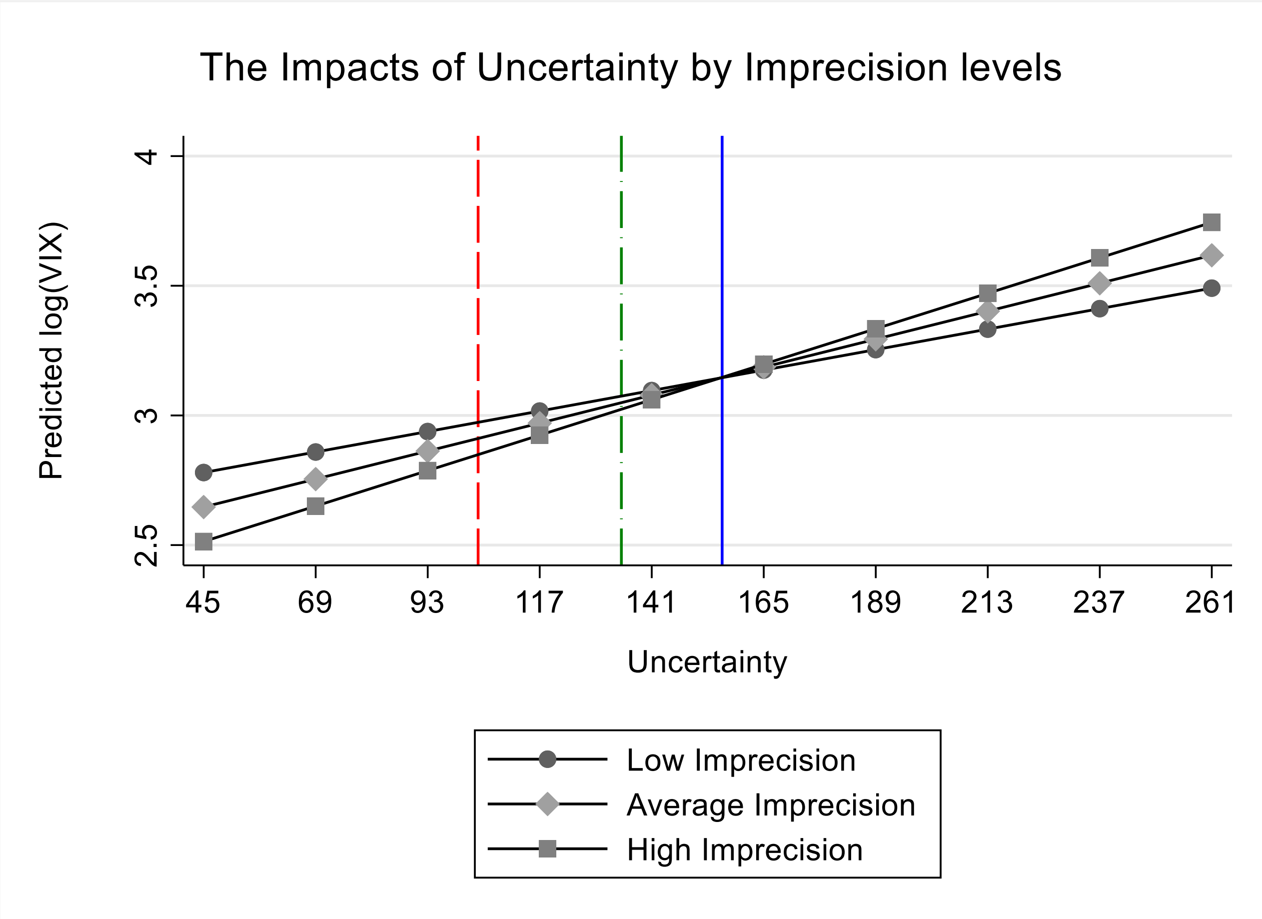
[37] As robustness tests, I also examine the effects of interaction terms using results in other columns and tables with controls for all the factors. The findings on interaction effects are consistent across different columns of results and are available upon request.

certain high level (see Figure 2.3).[38] Overall, these findings show that the VIX is lower in an environment characterized by low-quality political signals most of the time. The period post the 2016 U.S presidential election was characterized by a high level of policy uncertainty together with imprecise political signals in 2017; thus, in line with the results I expect to observe a low level of the VIX.

[38] Based on the results presented in specification (3), Table 2.6, the break-even level of *Uncertainty* for *Imprecision* is found to be 156.09.

Figure 2. 3

Effects of the Quality of Political Signals and Policy Uncertainty on the VIX



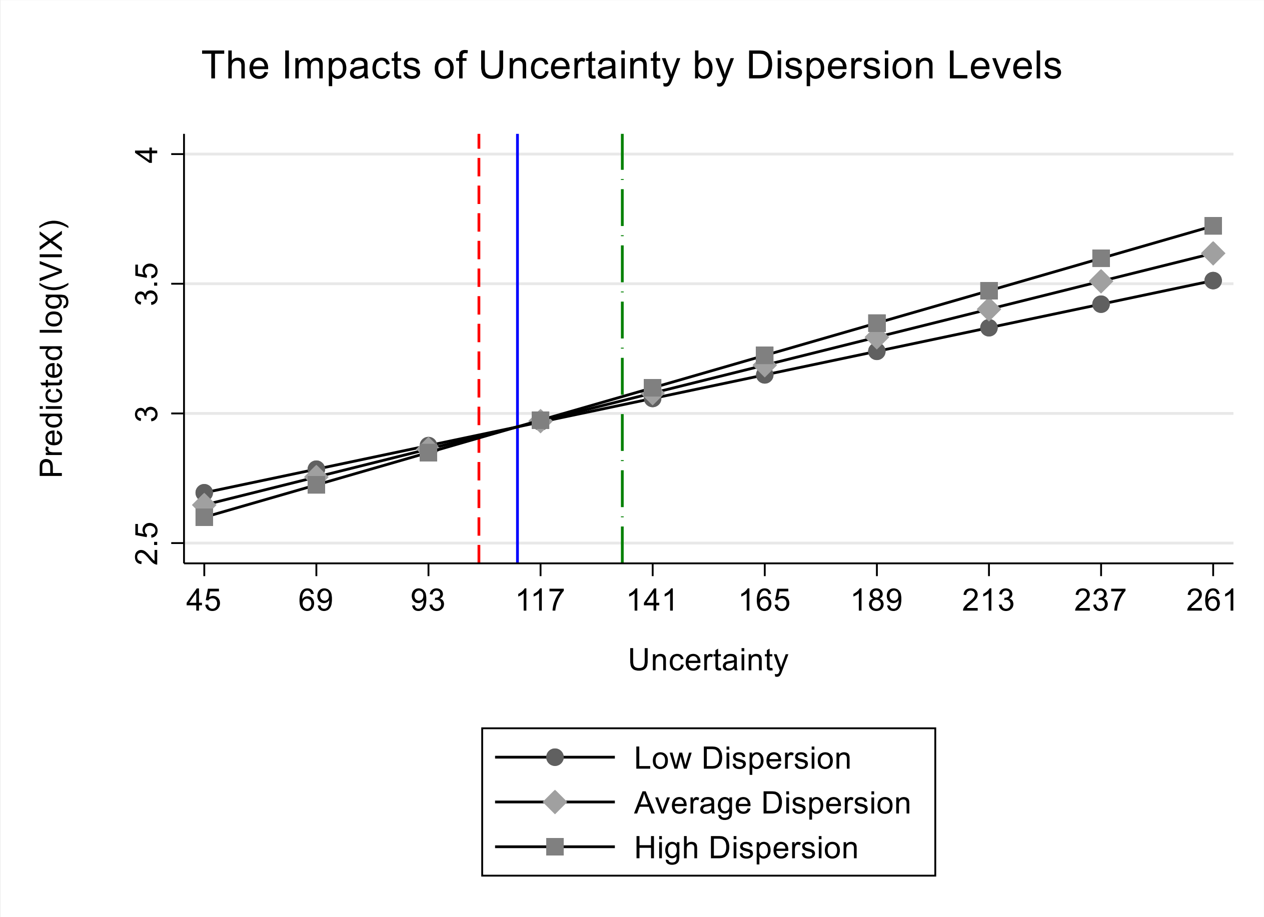
This figure presents the interaction effects of the quality of political signals and policy uncertainty on the VIX by showing how *Uncertainty* affected the predicted log value of the VIX conditionally on the low, average, and high levels of *Imprecision*. *Uncertainty* is the value of the BBD news-based uncertainty index. *Imprecision* is the measure for the quality of political signals, which is calculated as the three-month rolling volatility of the daily returns of the BBD daily index. The low level of *Imprecision* is calculated as its mean minus the standard deviation, while the high level is calculated as the mean plus the standard deviation. The red line illustrates the 97-16 median level of *Uncertainty;* the green line illustrates the 2017 median level of *Uncertainty;* the blue line illustrates the break-even level of *Uncertainty* for *Imprecision* as 156.09.

I next examine the impacts of policy uncertainty and opinion divergence (*Dispersion*) on the VIX. Similarly, I test the interacted effects of policy uncertainty conditionally on the low, average, and high levels of *Dispersion* as a defined variable. The low level of *Dispersion* is calculated as its mean minus the standard deviation (0.10), while the high level is calculated as the mean plus the standard deviation (0.33). I use again the results reported in specification (3) of Table 2.6, and prepare Figure 2.4. It presents the effects of *Uncertainty* on the logarithm of the VIX conditionally on those three levels of *Dispersion*. I denote the median level of *Uncertainty* over 1997–2016 (103.8) and its median level in 2017 (134.5). As shown in Figure 2.4, *Uncertainty* has a positive effect on the VIX independently for all three levels of *Dispersion*. Around the median levels of *Uncertainty* over 1997–2016, the VIX is found higher when *Dispersion* is lower, indicating that the VIX tends to be high in an environment characterized by high opinion divergence. These findings partly support the hypothesis (H2-2) and the literature claiming that higher opinions disagreement leads to higher market volatility (e.g. David, 2008, Dumas, Kurshev, and Uppal, 2009, Andrei, Carlin, and Halser, 2015) conditionally on a relatively low level of policy uncertainty. On the other hand, when *Uncertainty* is above a certain level, such a relationship between the VIX and opinion divergence is reversed: the VIX tends to be lower when investors' opinion disagreement is high (proxied by a low value of *Dispersion*).[39] Given the level of *Uncertainty* in 2017, the VIX is found lower when *Dispersion* is low, indicating that the VIX tends to be low in an environment characterized by high opinion divergence.

[39] Using the results presented in Column 1, Table 2.6, the break-even level of *Uncertainty* for *Dispersion* is found to be 112.05.

Figure 2. 4

Effects of Investors' Opinion divergence and Policy Uncertainty on the VIX



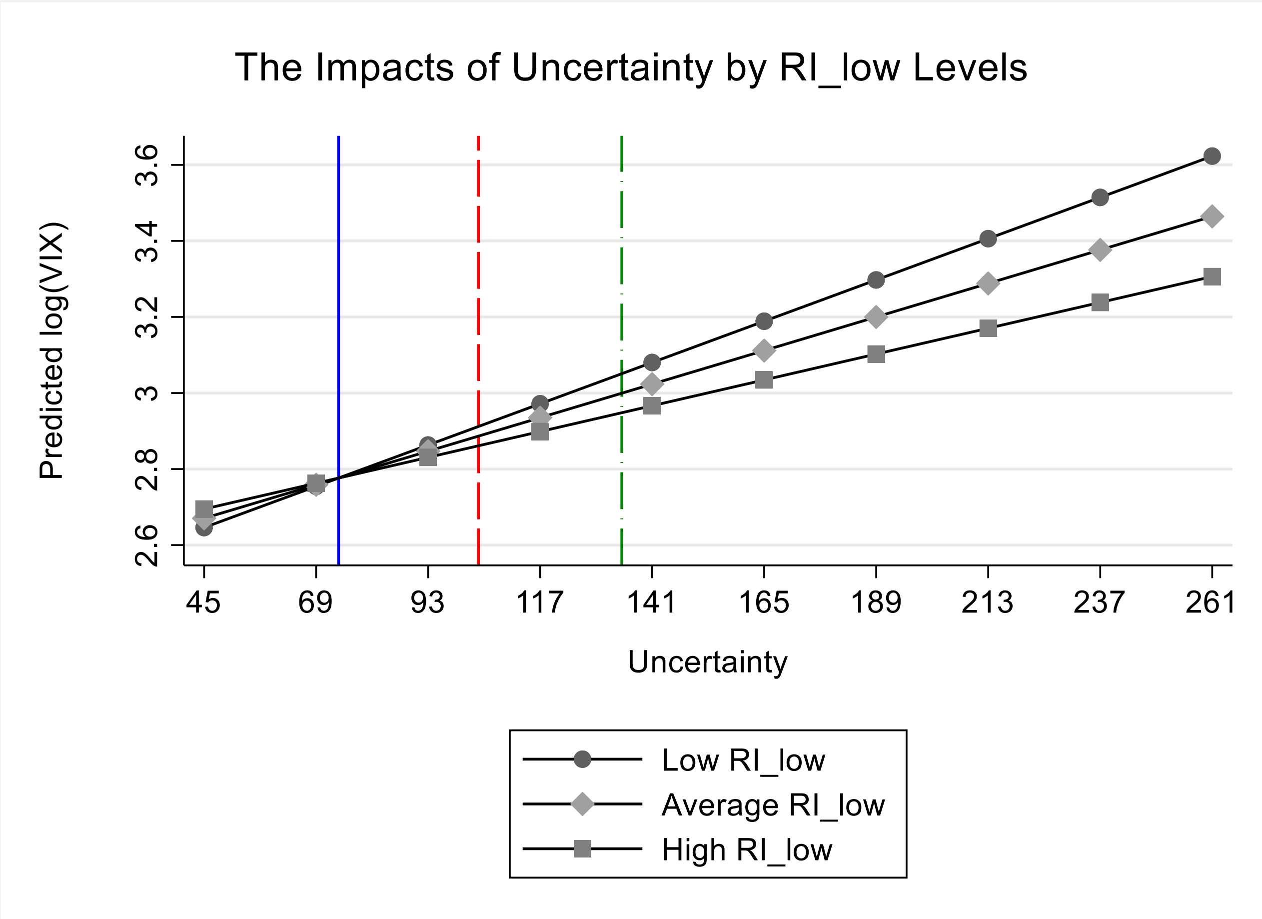
This figure presents the interaction effects of the opinion divergence and policy uncertainty on the VIX by showing how *Uncertainty* affected the predicted log value of the VIX conditionally on the low, average, and high levels of *Dispersion*. *Uncertainty* is the value of the BBD news-based uncertainty index. *Dispersion* is the measure for investors' opinion divergence, calculated as the difference between the highest AAII sentiment percentage and the lowest AAII sentiment percentage. The low level of *Dispersion* is calculated as its mean minus the standard deviation, while the high level is calculated as the mean plus the standard deviation. The red line illustrates the 97-16 median level of *Uncertainty;* the green line illustrates the 2017 median level of *Uncertainty;* the blue line illustrates the break-even level of *Uncertainty* for *Dispersion* as 112.05.

Finally, I present the effects of policy uncertainty conditional on the values of *RI_low* in Figure 2.5. As shown, the VIX tends to be lower when the representativeness bias is higher in a low-volatility environment given the median level of *Uncertainty* over1997-2016 and in 2017. This suggests that the positive impact of policy uncertainty on the VIX is weakened when likelihood of representativeness bias is high in recent low-volatility period. Considering the long bullish spell and low volatility in 2017, the results suggest a relatively low VIX.

This analysis of the interaction effects shows that given the level of policy uncertainty in 2017, the VIX tends to be low in an environment characterized by imprecise political signals, high opinion divergence and representativeness bias. These findings are consistent with the observed low level of the VIX in late 2016 and the whole of 2017.

Figure 2. 5

Effects of Representativeness and Policy Uncertainty on the VIX



This figure presents the interaction effects of the representativeness bias and policy uncertainty on the VIX by showing how *Uncertainty* affected the predicted log value of the VIX conditionally on the values of *LV*. *Uncertainty* is the value of the BBD news-based uncertainty index. *LV* is a dummy set to one if the latest one-month realized volatility is lower than the average monthly volatility in last 12 months.

2.5.5 Robustness test

For robustness tests, I employ alternative measures for each of the key explanatory variables. Specifically, I apply the two-month rolling volatility of the daily percentage changes of the BBD daily index (*Imprecision_2m*) as proxy for the quality of political signals. As alternative proxy for investors' opinion divergence, I consider the adjusted standard deviation of spot values of the AAII bullish, bearish, and neutral sentiment percentages (*Dispersion_SD*). More specifically, I adjusted AAII bullish, bearish and neutral sentiment by multiplying corresponding percentages by +1, -1 and 0, respectively to better capture the effects of bullish and bearish sentiments.[40] A dummy equal to one if the latest one month realized market volatility is lower than the volatility in last 12 months (*LV*) as proxy for representativeness bias. In addition, I apply the BBD overall index as a proxy for policy uncertainty. The results of robustness tests are presented in Table 2.7, where policy uncertainty is proxied by BBD news-based index (*Uncertainty*) in Panel A and by BBD overall index (*OverallBBD*) in Panel B.

As shown, the findings on the quality of political signals and options divergence are consistent with those reported previously. Though the coefficient of the alternative low volatility dummy (*LV*) and its interaction term are statistically significant and negative. This is consistent with the main results that the effect of policy uncertainty on the VIX is weaker in an environment characterized by greater probability of representativeness bias. Overall, those results indicate the findings are robust.

Additionally, to ensure that the empirical analysis is not subject to any potential multicollinearity issues, I tested the variance inflation factors (VIFs) for all the

[40] For instance, if sentiment percentages are expressed as (bullish, bearish, neutral), a case with (50, 50, 0) is expected to indicate more dispersion than (50, 0, 50) or (0, 50, 50). The old measure of the difference between the highest and lowest percentages, will be 23.6 for all of these. By adjusting with (+1, -1, 0) to compute the standard deviation of these outcomes, the case with (50, 50, 0) would yield a standard deviation of 40.8, but (50, 0, 50) or (0, 50, 50) would yield a standard deviation of 23.6.

independent variables. I excluded the interaction terms and regressed *log(VIX)* on the three explanatory factors together with the fundamental variables. The VIFs indicated that the independent variables do not present severe multicollinearity.

Table 2. 7 Robustness test

Panel A	(1)	(2)	(3)
$\Delta S\&P500_t$	-3.2077***	-3.0437***	-2.8217***
	(0.000)	(0.000)	(0.000)
Realized $Volatility_t$	0.5174***	0.53269***	
	(0.000)	(0.000)	
$Trend_t$	-0.0001***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)
$Uncertainty_t$	0.0002	-0.0008***	0.0018***
	(0.173)	(0.001)	(0.000)
$Imprecision\_2m_t$	-0.1380***		
	(0.000)		
$Uncertainty_t$ * $Imprecision\_2m_t$	0.0008***		
	(0.000)		
$Dispersion\_SD_t$		-1.1535***	
		(0.017)	
$Uncertainty_t$ * $Dispersion\_SD_t$		0.0102***	
		(0.017)	
LV_t			-0.0662**
			(0.017)
$Uncertainty_t$ * LV_t			-0.0011***
			(0.000)
$Imprecision_t$		-0.1200***	-0.3381***
		(0.000)	(0.000)
$Uncertainty_t$ * $Imprecision_t$		0.0007***	0.0020***
		(0.011)	(0.000)
$Dispersion_t$	-0.3485***		-0.4750**
	(0.000)		(0.013)
$Uncertainty_t$ * $Dispersion_t$	0.0029***		0.0044***
	(0.000)		(0.000)
Intercept	1.8641***	2.1446***	3.5963***
	(0.000)	(0.000)	(0.000)
Adj.R-squared	0.8151	0.8202	0.5508
N	5281	5281	5281

This figure presents the results of robustness tests. The dependent variable is the log value of the VIX. $Uncertainty_t$ is the value of the BBD news-based policy uncertainty index. $Imprecision\_2m_t$ measures of the quality of political signals, calculated as the two-month rolling volatility of the daily returns of the BBD news-based daily index. $Dispersion\_SD_t$ is the measure for investors' opinion divergence, calculated as the adjusted standard deviation of the AAII bullish, bearish, and neutral sentiment percentages. LV_t is a dummy set to one if the latest one-month realized volatility is lower than the average monthly volatility in the last 12 months. Other variables are defined as the same in previously reported results. Results are reported with Newey-West p-values. *,**,*** corresponds to statistically significance at the 10%, 5%, and 1% level, respectively.

Table 2.7 Robustness test (Cont'd)

Panel B	(4)	(5)	(6)
ΔS&P500$_t$	-3.1299***	-3.0025***	-2.7891***
	(0.000)	(0.000)	(0.000)
Realized Volatility$_t$	0.4975***	0.4896***	
	(0.000)	(0.000)	
Trend $_t$	-0.0001***	-0.0001***	-0.0002***
	(0.000)	(0.000)	(0.000)
OverallBBD$_t$	0.0012***	-0.0070***	0.0025***
	(0.000)	(0.000)	(0.000)
Imprecision_2m$_t$	-0.0787***		
	(0.001)		
OverallBBD$_t$ * Imprecision_2m$_t$	0.0006***		
	(0.005)		
Dispersion_SD$_t$		-2.7025***	
		(0.000)	
OverallBBD$_t$ * Dispersion_SD$_t$		0.0249***	
		(0.000)	
LV$_t$			-0.0762***
			(0.010)
OverallBBD$_t$ * LV$_t$			-0.0010***
			(0.000)
Imprecision$_t$		-0.1181***	-0.3650***
		(0.000)	(0.000)
OverallBBD$_t$ * Imprecision$_t$		0.0011***	0.0032***
		(0.000)	(0.000)
Dispersion$_t$	-0.5913***		-0.9748***
	(0.000)		(0.000)
OverallBBD$_t$ * Dispersion$_t$	0.0053***		0.0092***
	(0.000)		(0.000)
Intercept	1.8202***	2.7125***	3.5219***
	(0.000)	(0.000)	(0.000)
Adj.R-squared	0.833	0.840	0.629
N	5532	5281	5281

This figure presents the results of robustness tests. The dependent variable is the log value of the VIX. *OverallBBD$_t$* is the value of the BBD overall uncertainty index. *Imprecision_2m$_t$* measures of the quality of political signals, calculated as the two-month rolling volatility of the daily returns of the BBD news-based daily index. *Dispersion_SD$_t$* is the measure for investors' opinion divergence, calculated as the adjusted standard deviation of the AAII bullish, bearish, and neutral sentiment percentages. *LV$_t$* is a dummy set to one if the latest one-month realized volatility is lower than the average monthly volatility in the last 12 months. Other variables are defined as the same in previously reported results. Results are reported with Newey-West p-values. *,**,*** corresponds to statistically significance at the 10%, 5%, and 1% level, respectively.

2.6 Conclusion

Motivated by the extremely low level of the VIX and the relatively high economic policy uncertainty in the 14 months post the 2016 U.S presidential election, I examined the factors affecting the relationship between those two situations. I found that the combination of investors' representativeness bias, quality of political/economic signals, and investors' opinion divergence influences the link between the fear gauge and economic policy uncertainty. A recent low-volatility environment as the proxy of representativeness bias weakens the positive correlation independently on the level of economic policy uncertainty. In the case of the other two factors affecting the examined relationship, their impacts depend on the overall level of economic policy uncertainty. These findings are consistent with the implications of the theoretical models of Pastor and Veronesi (2013) and Dumas, Kurshev, and Uppal (2009) respectively, conditionally on a low level of policy uncertainty. In light of the results, the record low level of implied volatility in 2017 was caused by low realized market volatility accompanied by one of the longest bullish spells and the stream of unprecise economic/political signals together with high investors' opinion divergence.

To sum up, I find that the commonly accepted positive relationship between the VIX and economic policy uncertainty is affected by these three identified factors and is subject to changes over time.

Chapter 3

Derivatives, bank risk, and the Dodd-Frank Wall Street Reform Act

Abstract

This study investigates the impacts of the introduction of the Dodd-Frank Wall Street Reform Act (DFA) on U.S. bank holding companies. By examining 157 large U.S. bank holding companies, I find that in the post-DFA period, banks' contribution to systemic risk was substantially reduced. Moreover, I document that in the regulatory environment defined by the DFA, banks' use of interest and credit derivatives contributed less to systemic risk. On the other hand, the scrutiny reveals that banks experienced increased credit and overall risks following the commencement of the DFA.

Keywords: U.S. bank holding companies; Systemic risk; Dodd-Frank Wall Street Reform Act (DFA); Credit derivatives; Interest derivatives; Hedging; Global financial crisis

JEL codes: G11, G23

3.1Introduction

The popularity of derivatives products among financial institutions has led to a substantial growth in the derivatives market. The notional principal amount of financial derivatives held by U.S. bank holding companies (BHCs) rose from less than $18 trillion in 1995 to nearly 270 trillion by the end of 2012, which was more than 10 times the total asset value of BHCs.[41] Credit default swaps (CDSs) were used widely to transfer credit risk among financial institutions. The outstanding amount of CDSs grew from less than $1 trillion at the beginning of 2001 to over 6 trillion by the end of 2007. Empirical studies suggest that derivatives such as CDSs increase the correlations among banks, generate a wide net of linkages in the financial system, and make the financial market more vulnerable (Bedendo and Bruno, 2012). According to the Financial Crisis Inquiry Commission (2011), the significant systemic risk that fueled the global financial crisis (GFC) can be attributed to the size and complexity of the over-the-counter (OTC) derivatives market. Millions of derivatives contracts in such unregulated markets created interconnectedness among financial institutions and exposed the financial system to a contagion of losses and defaults via the counterparty credit risk channel.

As the financial crisis unfolded in the U.S. in 2007, the Democratic-dominated Congress pushed for more restrictive regulations on Wall Street. The Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) was signed into U.S. federal law on 21 July 2010. Title VII of the DFA – Wall Street Transparency and Accountability – requires that financial derivatives be cleared through a derivatives clearing organization. This title aims at improving market transparency and lowering the counterparty risk associated with financial derivatives products via a central clearing channel. Unlike the previously unregulated OTC derivatives market, where the network of exposure is highly dispersed, derivatives clearing organizations centralize the network of exposure and play a key role among counterparties involved in derivatives contracts. Derivatives clearing organizations are able to curtail the direct interconnectedness among banks by setting strict requirements on margins and collateral for

[41] Data retrieved from the Federal Reserve Bank of Chicago, https://www.chicagofed.org/applications/bhc_data/bhcdata_index.cfm

cleared derivatives (Singh, 2010). Derivatives clearing organizations also monitor the creditworthiness and risk of involved banks and observe the prices of transactions. With relevant information, derivatives clearing organizations can provide price quotes relying on involved banks for marking positions, which makes a cleared market less likely to freeze in states of market stress (Ghamami and Glasserman, 2017). Moreover, regulators are able to monitor the OTC derivatives market through derivatives clearing organizations instead of a diffuse network of bilateral transactions. However, the central clearing channel has been criticized, since the central clearing organizations with concentrated risk might ultimately require government support in a crisis. There are also debates on the extent to which the intended benefits of a central clearing channel could be achieved in practice.

Another key part of the DFA is the proprietary trading restrictions, known as the Volcker Rule, which prohibits government-insured banks from undertaking short-term risky trading of securities, derivatives, commodities futures, and options. The Volcker Rule directly requires reduction of banks' holdings of derivatives for speculation purposes, thereby mitigating their contribution to systemic risk (Li and Marinč, 2017).

Whether the DFA has achieved its intended objectives is a matter of controversy. On the one hand, the passing of the DFA paved the way to a regulatory scheme for previously unregulated OTC derivatives. Consumer advocates who strongly support the DFA agree that banks should not use federally insured deposits to gamble and take risky bets, and that banning proprietary trading will curtail risk-taking activities in the financial system. On the other hand, financial institutions have criticized the DFA for inadequately addressing the problems that really push the financial market into turmoil (Kane, 2012). It's also argued that the Volcker Rule requires joint rulemaking from five different agencies and is too complex to execute (Kane, 2012). The DFA is particularly too restrictive for smaller banks, which have assets in the range of $50 billion and are relatively too small to threaten the soundness of the financial system. The DFA creates substantial compliance costs (Gorman, 2017) and fails to achieve its stated objectives (Calomiris, 2017).

In early 2017, the Financial CHOICE Act was introduced in the 115th U.S. Congress to repeal many parts of the DFA. The CHOICE Act passed the Republican-led House on 8 June 2017. While the banking industry generally applauds the bill, the Democrats criticize the rolling back of the DFA as "a big bank-inspired wish list" (Schmidt and Dexheimer, 2017). The CHOICE Act would loosen the restrictions on banks' investments in private equity and hedge funds, and allow smaller banks to increase lending by minimizing a rule about qualified mortgages. Proponents of the CHOICE Act, which would repeal the Volcker Rule completely, argue that distinguishing between speculation and market timing is not simple and easy. On the negative side, the CHOICE Act proposes "one-size-fits-all" solutions which could be too weak to regulate large systemic banks. It exempts all banks which have substantial tangible equities in relation to their assets (at least 10 percent), from many regulatory rules applied under the DFA. Large systemic banks are typically highly interconnected, have opaque financial leverage, and large complicated off-balance-sheet derivatives positions. The letter by Americans for Financial Reform has pointed out that the simple capital ratio requirement of 10 percent proposed in the CHOICE Act is too low to serve as a cushion for mega banks; repealing the Volcker Rule would also invite more risky bets from systemically important financial intuitions, which is likely to fuel a more severe crisis and heighten its potential damage.

The recent debate on deregulations in the financial system and the proposed dismantling of the key aspects of the DFA raises the need for an extensive study as to whether the DFA has been effective in mitigating banks' risk and the degree of correlations among banks via derivatives use channels. Studies have investigated the impacts of derivatives, for example, interest rate derivatives on banks' risk and performance (Gunther and Siems, 2002; Li and Yu, 2010; Brewer, Deshmukh and Opiela, 2014). However, few studies on banks' risk have examined the interactions between banks' derivatives use and the passage of the DFA. Li and Marinč (2017) explore the impact of the mandatory clearing requirement and place emphasis on banks' holdings of interest rate derivatives.

In this study, I conduct an extensive study of 157 large BHCs in the U.S. and investigate two types of derivatives which have been widely used in the financial market: credit derivatives and interest rate derivatives. Interest rate derivatives holding is then categorized by hedging and trading purposes, which allows me to test the effectiveness of the channel of restricting the proprietary trading in the Volcker Rule. In addition, I categorize banks' holdings of interest rate derivatives by the trading approaches of OTC trading and exchange trading. By doing so, I test the effectiveness of the central clearing channel in Title VII of the DFA. I examine the effects of these derivatives holdings, the passage of the DFA, and their joint effects on three aspects: (i) banks' contribution to systemic risk, (ii) banks' risk, and (iii) banks' performance.

I find evidence that excessive use of interest rate derivatives for hedging, interest derivatives traded on exchanges, and credit derivatives (traded OTC) substantially increased banks' contribution to systemic risk. I also show that, in post-DFA periods, banks' contribution to systemic risk was significantly lower within two out of three proxies employed for systemic risk. Moreover, I document that use of credit and interest rate derivatives for hedging have weakened impacts on systemic risk in post-DFA periods, while the use of interest rate derivatives held for trading does not exhibit significant impacts on systemic risk either before or after the introduction of the DFA. Part of the results also shows evidence that use of derivatives and the DFA led to higher bank risks, and banks had a worse performance after the signing of the DFA.

The research contribution is three-fold. First, I examine credit derivatives and interest rate holdings categorized by hedging and trading purposes and by trading approaches of OTC trading and exchange trading. I extend the evidence on the channels through which banks' derivatives use affects their financial health and the wide net of linkages in the financial system. Second, by examining the effects of the DFA on systemic risk, banks' risk, and banks' performance through proprietary trading and central clearing channels, I shed light on whether the DFA has achieved its stated objectives in mitigating the degree of interconnectedness and improving the soundness of large financial institutions. Third, I use a more extensive set of variables than those that have been used in prior work. I capture banks' exposure to the housing market in each state and the degree of competition in the banking sector in each state. This analysis also examines banks' use of the discount window borrowing and four special capital programs. The study contributes to the limited literature on derivatives use and risk management in the banking system following the coming into effect of the DFA. The findings provide important implications to financial institutions, regulators, and legislators on the effectiveness of the DFA in regulating large systemic banks.

In the next section, I discuss the literature and develop the hypotheses. Section 3 summarizes the methods and data, Section 4 presents empirical results, Section 5 reports sensitivity analyses, and Section 6 concludes.

3.2 Literature and Hypotheses

This chapter looks at the two main streams of the literature: first, to examine the effects of derivatives holdings on systemic risk and banks' risk; and second, to evaluate the effectiveness of the DFA in curtailing the degree of interconnectedness among banks and improving the financial soundness of individual banks. The following analysis will briefly discuss the two relevant streams of literature.

3.2.1 Derivatives holdings, systemic risk, and DFA

The strong growth of derivatives holdings among banks has been a key driver of increasing claims within the financial system (Mayordomo, Rodriguez-Moreno, and Pena, 2014). Banks' off-balance-sheet activities such as derivatives use provide diversification benefits. However, such diversification benefits could also provide banks more incentives to actually take more risk, holding less capital and granting more loans, which increases the volatility of operating revenues, and consequently raise banks' contributions to undiversifiable systemic risk (Calmes and Theoret, 2010). The use of derivatives, as a type of non-resalable instrument, also causes credit chains among banks, leading to a higher degree of interdependence among banks and therefore increasing systemic risk (Bedendo and Bruno, 2012; Donaldson and Micheler, 2018). Previous studies suggest that the risk transfer via credit derivatives channels such as CDSs and collateralized loan obligations (CLOs) builds up a network among banks, and the flow of risk in such a network could lead to higher systemic risk (Nijskens and Wagner, 2011; Mayordomo et al, 2014; D'Errico, Battiston, Peltonen, and Scheicher, 2018).

Additionally, banks broadly use interest rate derivatives, particularly interest rate swaps, to enhance their interest rate risk exposure (Hirtle, 1997; Brewer, Minton and Moser, 2000; Carter and Sinkey, 1998). It's argued that even if banks are able to anticipate the interest rate policy, it is likely that they cannot adjust the debt exposure; however they can restrict the cost of debt by adjusting the interest rate derivatives exposures (Christoffersen, Nain and Oberoi, 2009). As a consequence, a higher cost of greater interest rate volatility during economic downturns is translated into systemic liquidity pressure on banks, leading to higher system risk (Mayordomo et al, 2014; Bakoush, Gerding, and Wolfe, Simon, 2017). Evidence has also been found that both use of interest rate derivatives for trading and use of interest rate derivatives for hedging increased banks' systemic risk (Li and Marinc, 2014). In light of the literature, I put forward the following hypothesis[42]:

H3-1a: ***Banks' holdings of derivatives increase their contributions to systemic risk.***

The findings on the effectiveness of the DFA in mitigating systemic risk are mixed. The central clearing with collateral requirements under the DFA could effectively limit the lack of position transparency in OTC derivatives (Acharya and Bisin, 2014). By improving the transparency in derivatives' trading, the central clearing under the DFA was able to restrict the shortfall losses, and consequently lower counterparty and systemic risks in the financial network built up by derivatives (Amini, Filipovic, and Minca, 2013; Loon and Zhong, 2014). In addition to the central clearing, the Volcker Rule, that limits bank's proprietary trading activities, effectively targeted institutions that engage in risky activities and mitigated systemic risk (Elayan, Aktas, Brown, and Pacharn, 2018).

On the other hand, central clearing under the DFA could increase the counterparty risk because of the information asymmetries between central clearing counterparties and large financial institutions, since central clearing counterparties have a disadvantage in evaluating clearing members' risk and therefore could underestimate the risk, and thereby weaken its guarantee (Pirrong, 2009). It has also been argued that the central clearing required by the DFA

[42] All the hypotheses in Chapter 3 are listed in Appendix 4.1.

might not be able to further lower the counterparty risk if the existing arrangements in the OTC derivatives market (e.g. posting of collateral by both counterparties, use of the International Swaps and Derivatives Association, master agreements, and credit support annexes) can effectively deal with counterparty risk (Arora, Gandhi, and Longstaff , 2012) . Even though the DFA intends to reduce systemic risk via the central clearing of OTC derivatives at central clearing counterparties, these counterparties themselves can create, or contribute to, systemic risks (Duffie and Zhu, 2009; De Genaro, 2016). Cont (2017) tests the impacts of OTC derivatives' central clearing under the DFA and shows that central clearing did not reduce systemic risk, but transformed counterparty risk into liquidity risk via margin calls, since negative cash flows due to the margin requirements draw out the liquid resources of market participants.

In addition to the studies discussed above that examined the impacts of the DFA on systemic risk, there are only a few studies linking the effectiveness of the DFA in mitigating systemic risk with banks' derivatives use. Li and Marinč (2017) test the effects of the mandatory clearing requirement under the DFA and document that following the introduction of the mandatory clearing requirement, there was a drop in systemic risk associated with interest rate derivatives. However, their findings show that banks' use of CDSs reduced their contribution to systemic risk before the introduction of the mandatory clearing requirement, and CDSs' use even increased systemic risk after mandatory clearing. This finding is not consistent with the expectation of markets and regulators, and is not explained in their study. In their estimation models, they do not consider the effects of terms such as loans to other depository institutions and balance due from other depository institutions, which are directly related to banks' interconnectedness and systemic risk. The effects of an event dummy for mandatory clearing are also excluded. Gao, Liao, and Wang (2018) examine banks' systemic risk before and after the passage of the DFA with cross-sectional data and present evidence that systemic risk among banks significantly decreased following the passage of the DFA. They also analyze the effect of credit derivatives' use by banks on systemic risk and find insignificant results. However, they only examine credit derivatives written/sold by banks without considering credit derivatives purchased and interest rate derivatives. They also do not include the terms directly related to banks' interconnectedness and systemic risk in their regression models.

I conjecture that the implementation of the DFA, specifically the Volcker Rule, leads to a lower degree of derivatives use, thereby reducing the interdependence among banks. I share the same view as Singh (2010) and Li and Marinč (2017) that implementing the mandatory clearing requirement improves the transparency in the derivatives markets, therefore curtailing the effects of banks' derivatives holdings on systemic risk. Thus, I put forward the following hypothesis:

H3-1b: ***The implementation of the DFA mitigates banks' contribution to systemic risk.***

H3-1c: ***The implementation of the DFA reduces the impacts of derivatives holdings on banks' contribution to systemic risk (in H3-1a).***

3.2.2 Derivatives holdings, banks' risk and banks' performance

3.2.2.1 Derivatives holdings and bank risk

Derivatives have been widely used by financial institutions to hedge against unfavorable changes in the value of their cash flows. Derivatives help mitigate cash flow volatility, lower external funding costs, and reduce banks' overall risk (Koppenhaver, 1985; Froot, Scharfstein and Stein, 1993; Duffee and Zhou, 2001; Jaffe, 2003; Norden, Buston, and Wagner, 2014; Bartram, 2017; Deng, Elyasiani, and Mao, 2017; Huang, Kabir, and Zhang, 2017).

Previous studies, however, show that banks are more likely to use financial derivatives for trading motives rather than for hedging purposes (Minton, Stulz and Willamson, 2005; Li and Marinč, 2014). This tendency makes them more vulnerable to financial distress (Li and Marinč, 2014). Without proper oversight, derivatives traders may take a position which is substantially larger than their risk-absorbing capacity (Biais, Heider, and Hoerova, 2012). Derivatives used for regulatory arbitrage to decrease capital requirements may also lead to excessive risk taking (Yorulmazer, 2013). It could also be possible that banks use derivatives for hedging to mitigate their exposure to tradable risk in order to take greater credit risk and earn higher economic rents (Deng, Elyasiani, and Mao, 2017). Supportive evidences have been found by Deng, Elyasiani, and Mao (2017), Ghosh (2017), Titova, Penikas, and Gomayun (2018) that the use of derivatives for hedging by banks could induce higher banks' risk. In light of the above literature, I propose the following hypothesis:

H3-2a: ***Both interest rate derivatives used for trading and hedging increase banks' risk.***

Credit derivatives, such as CDSs and CLOs, have been widely used by financial institutions to transfer counterparty credit risks. Despite being powerful hedging tools, they are like a double-edged sword. Credit derivatives, which are similar to an insurance policy, may increase moral hazards as it lowers banks' motivations to thoroughly review loan applications and regularly monitor bank loans (Parlour and Winton, 2013). Banks which hold CDSs to hedge against potential credit loss tend to make more profits by raising loan volumes while taking a higher degree of risk (Acharya and Naqvi, 2012; Shan, Tang, and Yan, 2014). In light of the literature above, I propose the following hypothesis:

H3-2b: ***Credit derivatives increase banks' risk.***

There are a few studies in the empirical literature that link banks' individual risk to derivatives traded in the OTC market and on exchanges. Banks using derivatives traded in OTC markets are more likely to become associated with higher risks because derivatives used for speculating and trading purposes in the OTC market could increase banks' risk exposure (Li and Marinč, 2014). The low levels of transparency, supervision, and monitoring in the OTC market might also allow banks to hedge very risky positions, which can hardly be allowed or are extremely costly to hedge in more transparent markets. On the contrary, derivatives traded on exchanges with a higher level of transparency are more likely to be used for hedging purposes by banks. Thus, I put forward the following hypothesis:

H3-2c: ***Derivatives traded in OTC markets increase banks' risk, while derivatives traded on exchanges decrease banks' risk.***

While the Volcker Rule limited banks' proprietary trading activities, which reduced the size of their trading books, banks could still acquire more risk behaviors via other approaches such as raising the illiquid book portfolios, which are hard to control (Chung, Keppo, and Yuan, 2016). As a result, the DFA is likely to be not effective in reducing banks' risk-taking behavior, and banks could even exhibit higher volatility in asset returns after the DFA was signed (Keppo and Korte, 2016). Additionally, the liquidity reduction attributed to the DFA could hinder banks' ability to meet short-term obligations and makes them more susceptible to financial distress (Mohanty, Akhigbe, Basheikh, and Khan, 2018). Thus, I propose the following hypothesis:

H3-3: ***The implementation of the DFA increases banks' risk.***

3.2.2.2 Derivatives holdings and bank performance

Banks that use derivatives for speculation purposes tend to achieve higher returns, although those trading activities expose banks to a higher degree of risk (Li and Yu, 2010; Lau, 2016). While there are a few studies reporting that the use of derivatives did not improve the banks' performance (Keffala and De Peretti, 2016; Egly and Sun, 2014), the majority of previous studies present evidence that derivatives use by banks are positively correlated to banks' profitability and performance (e.g. Said, 2011; Chang, Ho, and Hsiao, 2018). I share a similar view with Said (2011), and propose the following hypothesis:

H3-4: ***Derivatives holdings improve banks' performance.***

The DFA restricts consumer credit, makes mortgages and bank transactions more expensive, increases banks' compliance costs, and reduces banks' liquidity. It also limits the financial sector's ability to innovate. Previous studies suggest that the DFA decreases the capacity and quality of banks' market-making services (Chow and Surti, 2011; Whitehead, 2011; Duffie, 2012), therefore lowering banks' performance. Schäfer, Schnabel, and Weder (2015) present evidence that the DFA significantly reduces banks' share returns. Similar results have also been found by Chung, Keppo, and Yuan (2016), Keppo and Korte (2016), and Gao, Liao, and Wang (2018). Shen and Hartarska (2018) find that derivatives use by banks reduces the sensitivity of profitability to credit risks and improves profitability. They also argue that the Volcker Rule imposed high compliance costs and may have negative impacts on the profits of banks. In light of the literature discussed above, I propose the following hypothesis:

H3-5: ***The implementation of the DFA decreases banks' performance.***

3.3 Methodology

In this section, I present the measures of banks' contribution to systemic risk, banks' risks and performance. I then present the models used to test the null hypothesis formulated above. The section is divided into two parts: the first part shows measures and models of banks' contribution to systemic risk, and the second part presents those for banks' risk and performance.

3.3.1 Banks' systemic risk

I consider conditional value at risk as a proxy for the contribution of each bank to the systemic risk. Following Adrian and Brunnermeier (2011), I calculate the *Value at Risk* of the banking system conditional on the distress of bank *i* with a confidence level of 95 percent (*CoVaR*(5%)) and also the *Value at Risk* of the banking system with a confidence level of 50 percent, which is conditional on the median state of the bank (*CoVaR*(50%)). Therefore, bank *i*'s contribution to systemic risk is estimated as the difference between those two conditional *Value at Risks* (*ΔCoVaR*) of the banking system.

In order to calculate *ΔCoVaR*, *I* first estimate the growth rate of the market value of total assets of bank *i* at time *t*, X_t^i. The market value of total asset is calculated as the product between the market value of bank *i*'s equity and the bank's ratio of total assets to book equity. X_t^i is then calculated as the percentage change of the market value of total asset.[43] The next

[43] I calculate X_t^i in a similar way as Adrian and Brunnermeier (2011): $X_t^i = \frac{ME_t^i \cdot LEV_t^i - ME_{t-1}^i \cdot LEV_{t-1}^i}{ME_{t-1}^i \cdot LEV_{t-1}^i}$, where *ME*

step is to calculate the time-variant *Value at Risk* (*VaR*) for a bank and the *CoVaR* of the banking system conditional on the distress of that bank. I follow Adrian and Brunnermeier (2011) and Mayordomo, Rodriguez-Moreno and Peña (2014), and employ the means of quantile regression (Koenker and Bassett, 1978) to estimate the coefficients (α, β, γ) in the following regressions:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^t \tag{3.1a}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i}, \tag{3.1b}$$

where M_{t-1} is a set of state variables describing the current market situation, including the VIX, which is the index of implied volatility of the stock market tracked by the Chicago Board Options Exchanges; Liquidity Spread, which captures the difference between the three-month repo rate and the three-month bill rate; Changes in Three-Month Treasury Bill Rate; Changes in the Slope of the Yield Curve, measured by the yield spread between the 10-year Treasury rate and the three-month bill rate; Changes in the Credit Spread, measured by the credit spread between 10-year BAA-rated bonds and the 10-year treasury rate; Return of the S&P 500 Index and Real Estate Sector Return in Excess of the Market Return. Specifically, bank *i*'s *VaR(5%)* is estimated through the quantile regression with a 95 confidence level by using the coefficient ($\hat{\alpha}^i$, $\hat{\gamma}^i$) estimated in Equation (3.1a). Then the *CoVaR* of the banking system conditional on bank *i*'s distress is calculated with the estimated *VaR(5%)* of bank *i*, together with coefficient ($\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$, $\hat{\gamma}^{system|i}$) estimated through the quantile regression in Equation (3.1b). The process is presented as followings:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-1}. \tag{3.2}$$

where q is the quantile confidence level. Similarly, I apply the quantile regression with a

is the market value of equity and *LEV* is the ratio of book value of total asset to book equity value.

confidence level of 50 percent to calculated bank *i*'s *VaR(50%)* and the *CoVaR* of banking system conditional on bank *i*'s *VaR(50%).* Finally, the *ΔCoVaR* of bank *i* is calculated as the difference between the banking system's *Value at Risk* conditional on the distress of the bank *i* (*CoVaR* (5%)) and *Value at Risk* conditional on the median state of the bank *i* (*CoVaR* (50%)):

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%)$$
$$= \hat{\beta}_q^{system|i}(VaR_t^i(q) - VaR_t^i(50\%)) \tag{3.3}$$

A lower value (negative) in *ΔCoVaR* indicates a higher contribution to systemic risk.[44] The above constructed proxy of banks' systemic risk is a dependent variable in the panel regression designed to examine the effect of derivatives use and the introduction of the DFA on banks' contribution to systemic risk, the following model is estimated:

$$SR_{i,t} = \alpha_0 + \sum \beta_n Y_{i,p,t-1} + \sum \psi \ PostDFA + \sum \lambda_{ik} PostDFA * Y_{i,p,t-1} + \sum \gamma_m C_{i,t-1} + \varepsilon \,, \tag{3.4}$$

where $SR_{i,t}$ is the measure on banks' contribution to systemic risk initially measured by the change in conditional value at risk (*ΔCoVaR*); $Y_{i,t}$ is the notional value of credit derivatives and interest rate derivatives, categorized either by holding purpose (trading or hedging) or by trading approach (OTC or exchange); the event dummy, *PostDFA*, which is set to one after the introduction of the DFA and zero otherwise; and $C_{i,t-1}$ is the set of firm characteristics variables including banks' exposure to the housing market, HHI index, and government bailout programs dummy. According to the statement of the Financial Crisis Inquiry Commission (2011), as financial derivatives expose the financial system to a contagion of spreading losses and defaults, I expect negative signs for variables measuring the use of derivatives, $Y_{i,t}$, which suggests that derivative use by banks increases banks' contribution to systemic risk. If the DFA effectively

[44] The potential disadvantage of *CoVaR* is that under certain distributional assumptions about firm's returns, *CoVaR* treats two firms identically in terms of systemic risk if the firms have the same return correlation with the aggregate market, even though they might have very different sizes with different return volatilities (Acharya, Engle, and Richardson, 2012). It is caused by regressing the banking sector's return on that of individual bank, rather than the other way around. More specifically, a big bank and a small bank could have the same return correlation with the market, and therefore same *ΔCoVaR,* suggesting that these two banks have same contribution to systemic risk. This is apparently wrong, since the big bank contributed more to the systemic risk. To deal with this, I applied a subsample of big banks to test my research question; the results are discussed later in Section 3.5.

controls the impact of financial derivatives on systemic risk, I then expect positive signs for the interactions between the DFA dummy and the derivative variables. I control for the clustering and heteroskedasticity in standard errors at both the bank and time level in all regression estimates.

In order to address the potential critique that the results related to the DFA are driven by the selection of the proxy of banks' contribution to systemic risk, I consider two alterative measures as dependent variables in panel regression (3.4), namely marginal expected shortfall (*MES*) and banking industry beta. Marginal expected shortfall is defined as the average return of bank *i* on days when the banking industry (*S&P Banks Selected Industry Index*) return, R_m, is among its lowest 5 percent level in a one-quarter period:

$$MES_t^i = E[R_t^i | R_t^m \leq q] \quad , \tag{3.5}$$

where *q* stands for the quantile of *S&P Banks Selected Industry Index* return, which is set as 5 percent. Accordingly, a lower negative value in *MES* indicates a higher marginal contribution to systemic risk.

In addition, I apply banking industry beta as a third measure of systemic risk. Accordingly, a bank's industry beta is calculated as the sensitivity of stock return to the return of *S&P Banks Selected Industry Index* in a one-year time window. Higher industry beta could imply higher systemic risk (Nijskens and Wagner, 2011).

3.3.2 Banks' risk and performance

In order to test the impact of the DFA on the risk of individual U.S. BHCs, I consider different types of risks and their measures. As proxies of credit risk of U.S. banks, I use *Z-score* and *distance to default*. The *Z-score* is defined as the sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets:

$$Z\text{-}score = \frac{RoA + E/TA}{\sigma_{RoA}} \tag{3.6}$$

Z-score indicates the number of standard deviations that a bank's rate of return on assets can have in a single period before the bank becomes insolvent. I calculate *Z-score* using a time window of 16 quarters. A higher *Z-score* signals a lower probability of bank insolvency.

The other proxy of credit risk is *distance to default*, which measures the number of standard deviations the asset value is away from the default point. Consistent with Moody's KMV model, *Distance to default* is defined as

$$Distance\,to\,default = \frac{V-K}{\sigma_v}, \tag{3.7}$$

where V is the market value of total assets; K is the default boundary, calculated as short-term debt plus half of the long-term debt; and σ_v is the standard deviation in the market value of assets over 16 quarters.[45] Higher *distance to default* indicates less chance for default.[46]

In addition to credit risk, I employ other measures of banks' risks, namely the level of overall risk. Specifically, I calculate bank *i*'s volatility of its daily stock return within a six-month rolling window (*Volatility*) to capture overall risk . A higher *Volatility* indicates a higher risk.

In order to evaluate the impacts of derivatives use in the *pre* and *post* DFA regulatory environments on the banks' credit and overall risk, I consider the following model:

$$IR_{i,t} = \alpha_0 + \sum \beta_n Y_{i,p,t-1} + \sum \psi\ PostDFA + \sum \lambda_{ik} PostDFA * Y_{i,p,t-1} + \sum \gamma_m C_{i,t-1} + \varepsilon, \tag{3.8}$$

where $IR_{i,t}$ is the bank's risk measures, which could either be *Z-score, Distance to Default,* or *stock volatility* for BHC *i* and time *t*. $Y_{i,t}$ is the notional value of credit derivatives and interest

[45] As the market value of a bank's debt is not available, the market value of its total asset is derived as the book value of its total liability and the market value of its equity. This approach is similar to the approach underlying Moody's KMV model. The book value of a bank's total liability, including deposits, is collected from SNL database.

[46] I also test by using the *Distance to Default* with *RoA* as the drift component: (V-K+RoA)/ σ_v; the results still hold and are available upon request.

rate derivatives, categorized either by holding purpose (trading or hedging) or by trading approach (OTC or exchange). *PostDFA* is a dummy variable, which is equal to one after the DFA has been signed in the law and zero otherwise. $C_{i,t-1}$ is the set of bank-specific variables and can differ across regressions, as some variables are used to calculate the dependent variable and therefore cannot be included as explanatory variables.

Next, I analyze of the impacts of the DFA and derivatives use on the performance of U.S. banks. As proxies for banks' performance, I consider *Tobin's Q*, *returns on assets* (*ROA*), and *cost-to-income ratio*. Higher values in banks' *Tobin's Q* and *returns on assets* (*ROA*) indicate better performance, while higher *cost to income* suggests a lower operating efficiency and therefore a worse performance. The following model is used for the examination of bank performance:

$$PF_{i,t} = \alpha_0 + \sum_{p=1}^{N} \beta_n Y_{i,p,t-1} + \psi PostDFA + \sum_{p=1}^{N} \lambda_{ik} PostDFA * Y_{i,p,t-1} + \sum \gamma_m C_{i,t-1} + \varepsilon \quad , \qquad (3.9)$$

where $PF_{i,t}$ is the bank's performance measures, which could be either *Tobin's Q, ROA, or cost to income.* The definitions of other variables are the same as in Equation (3.8).

3.4 Data

3.4.1 Sample and data

This study examines large and publicly listed BHCs in the U.S. from the first quarter of 2007 to the last quarter of 2014. The study covers the subprime crisis 2007–2009, and roughly equal pre-DFA and post-DFA sub-periods. I focus on BHCs because these large financial institutions are more likely to use derivatives for both hedging and trading purposes. The main sample is restricted to banks which have at least $1 billion in assets at the end of 2006, and have derivatives holdings reported in the Y9 call report as well as stock prices reported in CRSP. The main sample consists of 157 BHCs, which captures more than 70 percent of the total market capitalization of U.S. publicly traded BHCs at the end of 2006.

Bank-specific data were collected from the SNL Financial database (SNL). The volatility of equity returns, which is based on six months of daily data, was calculated using stock prices data from CRSP. The banking industry index (*S&P Banks Selected Industry Index*) returns and macro-economic variables used to calculate *△CoVaR* were downloaded from Datastream.

3.4.2 Independent variables

I focus on two types of derivatives, namely interest rate derivatives (*IRDs*) and credit derivatives (*CDs*), which have been widely used by banks and subject to heightened regulations following the GFC (Li and Marinč, 2017). According to Accounting Standards SFAS133, banks must classify derivatives into two sub-categories: for hedging and for trading purposes.[47] I therefore examine separately banks' interest derivatives holdings for trading (*IRDs trading*) and interest derivatives holdings for hedging (*IRDs hedging*); each is measured as the notional amount of the relevant off-balance-sheet contracts reported in the Y9 call report, and then scaled by banks' assets.

In contrast to interest rate derivatives, credit derivatives holdings are not categorized based on the purposes. Thus, I follow a similar approach as in Li and Marinč (2014) and examine the net notional amount of credit derivatives scaled by banks' assets (*Net CDs*). By categorizing derivatives for trading or hedging purposes, I test the effectiveness of the proprietary trading channel through which the Volcker Rule under the DFA aims to mitigate the systemic risk associated with derivatives. Additionally, I calculate the total net notional amounts of interest rate derivatives categorized by whether they are traded OTC or on exchanges. More specifically, interest rate derivatives traded OTC (*IRDs OTC*) are calculated as the sum of the notional amount of interest rate forwards, swaps, and the net long positions in OTC interest rate options, while interest rate derivatives traded on exchanges (*IRDs exchange*) are calculated as the sum of the notional amount of interest rate futures and net long positions in exchange interest rate options. Given the credit derivatives reported in SNL are all traded in the OTC market, I get three derivative categories, namely interest rate derivatives traded OTC (*IRDs*

[47] Contracts held for trading purposes include those used in dealing and other trading activities accounted for at market value (or at lower of cost or market value) with gains and losses recognized in earnings.

OTC), interest rate derivatives traded on exchanges (*IRDs exchange*), and net credit derivatives (*Net CDs*). By doing this, I can examine the effectiveness of the central clearing channel in Title VII of the DFA on mitigating the systemic risk associated with OTC derivatives.

In addition to derivatives holdings, I employ two additional variables which capture the extent of interconnectedness among financial institutions: *Loan to depository institutions* and *Balance due from depository institutions* (scaled by *gross loans and leases*).[48] Mayordomo, Rodriguez-Moreno, and Pena (2014) found that *Balance due from depository institutions* increased banks' systemic risk, while the impacts of *Loan to depository institutions* were insignificant.

I create a dummy variable, *PostDFA*, for bank-quarter observations in the period following the signing of the DFA (July 21, 2010). To explore the joint effects between derivatives and the DFA, I first construct three interaction terms between interest rate derivatives held for hedging, interest rate derivatives held for trading, net credit derivatives, and the dummy, *PostDFA*, to test the effectiveness of the proprietary trading channel. I then construct the interaction terms between interest rate derivatives traded OTC (*IRDs OTC*), interest rate derivatives traded on exchanges (*IRDs exchange*), net credit derivatives (traded OTC), and *PostDFA* to test the central clearing channel of the DFA.

In terms of the other variables, I control for banks' *size*, *return on average assets* (*ROA*) to account for profitability, and *short-term borrowings* (scaled by assets). I also add *book-to-market* and idiosyncratic risk captured by stock return volatility in the models to capture banks' health and uncertainty.

Mayordomo et al. (2014) present evidence that *Non-performing loans* and *Leverage ratio* have greater impacts on systemic risk than derivatives holdings. In light of their findings, I incorporate *Loan loss provisions* and *Tier 1 risk ratio* in the models. I use *Loan loss provisions* as this measure is an allowance for potential loan losses, whereas *Non-performing loan* only

[48] Accordingly, interconnectedness measures the extent to which a bank is connected with other institutions in such a way that its stress could easily be transmitted to other institutions.

accounts for uncollected loans in the past. *Tier 1 risk ratio* is also a better measure than *Leverage ratio*. The latter simply sets the same risk weight across all assets, while *Tier 1 risk ratio* is derived based on risk-weighted assets, that is, it captures the quality of a bank's asset portfolio.[49]

The study period witnessed several failures and a number of mergers among financial institutions. I include merged banks in the sample as long as SNL reports its balance sheet and income items. For an acquirer, taking over near-failed firms will substantially raise its leverage and loan loss provisions. To capture this effect, I create a dummy variable for banks that made an acquisition in the quarter examined.

During the subprime crisis, many banks experienced financial distress due to their exposure to the housing bust and their substantial losses on real estate–related investments (Cole and White, 2012). I account for a bank's exposure to the downturn in the real estate market in each state where it operates. I calculate a weighted average housing return index for each bank-quarter. Housing returns are derived from the Fannie Mae house price index for each state. The weighted average is derived by using the proportion of deposits a bank has in each state, which is available from branch deposit and branch location data in SNL.

To capture the degree of market concentration in the banking sector, I follow Berger and Roman (2015) and construct a weighted average Herfindahl-Hirschman Index (HHI) for each bank-year in a similar manner. The weighted average HHI for each bank-year is derived by using the proportion of deposits a bank has in each state.

I also consider banks' use of the discount window borrowing and four special capital programs, namely the troubled asset relief program (TARP), term securities lending facility, term auction facility, and primary dealer credit facility. The data on special capital programs and discount window borrowing were collected from the Federal Reserve System.[50]

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[49] In a robustness analysis, I employ *Non-performing loans* and *Leverage ratio* as in Mayordomo et al. (2014). The key results are discussed in the robustness analysis section.

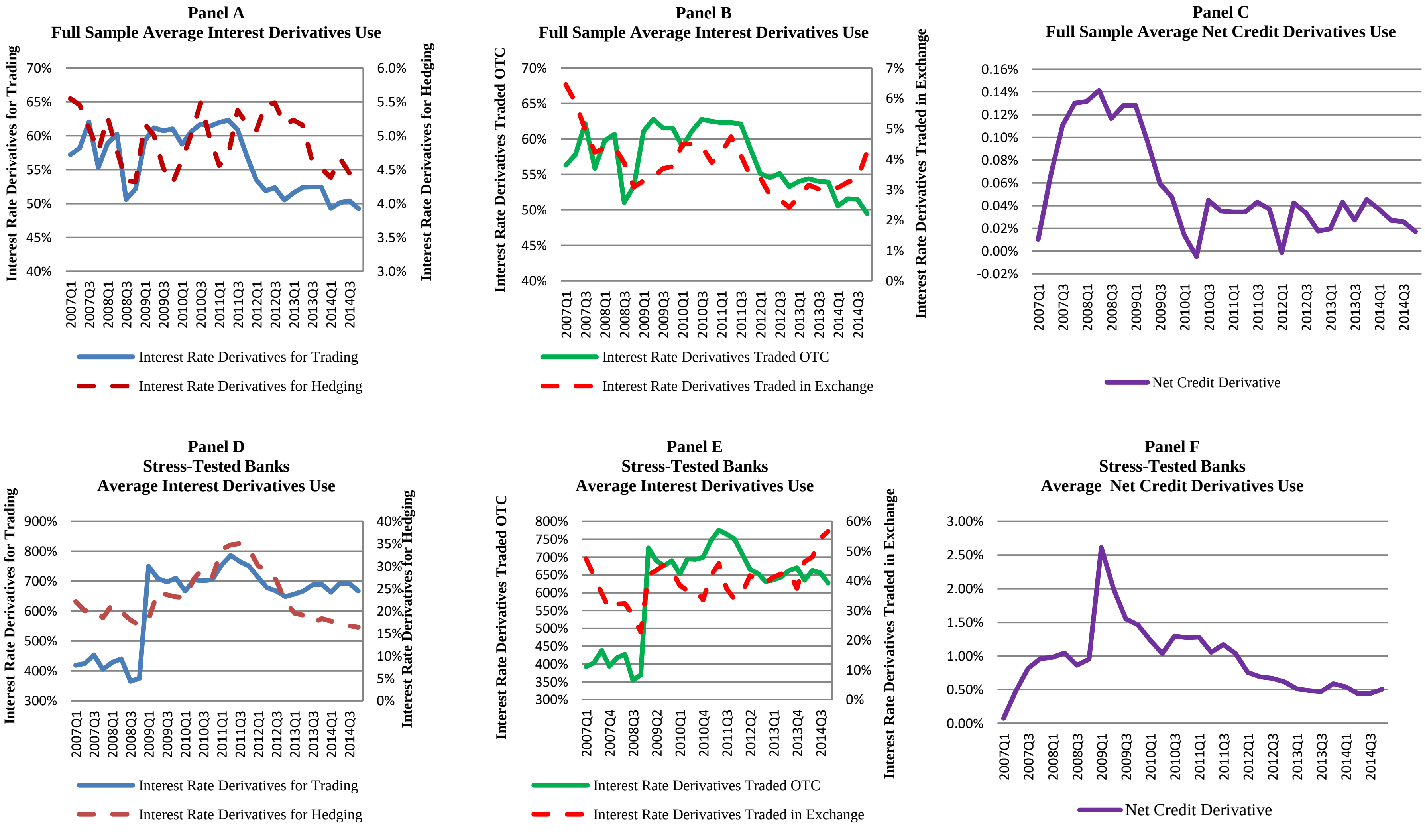
[50] Data source: https://www.federalreserve.gov/regreform/discount-window.htm

3.4.3 Statistics

Figure 3.1 features the average derivatives holdings (scaled by total assets) across quarters for the main sample of 157 banks (Panel A, B, C) and the alternative sample of 18 stress-tested banks (Panel D, E, F).[51] Panel A and Panel D feature the average interest rate derivatives holdings for trading and for hedging purposes, while Panel B and Panel E show the average

[51] A bank stress test is an analysis designed to test whether a bank has enough capital to withstand the impact of adverse economic developments. In the U.S., big banks are required to undergo stress tests conducted by the Federal Reserve. There were more than 18 banks that underwent stress tests in 2015. I get the sample of 18 banks due to data unavailability for some stress-tested banks.

Figure 3. 1



Panel A
Full Sample Average Interest Derivatives Use
Interest Rate Derivatives for Trading
Interest Rate Derivatives for Hedging
Interest Rate Derivatives for Trading
Interest Rate Derivatives for Hedging
Panel B
Full Sample Average Interest Derivatives Use
Interest Rate Derivatives Traded OTC
Interest Rate Derivatives Traded in Exchange
Interest Rate Derivatives Traded OTC
Interest Rate Derivatives Traded in Exchange
Panel C
Full Sample Average Net Credit Derivatives Use
Net Credit Derivative
Panel D
Stress-Tested Banks
Average Interest Derivatives Use
Interest Rate Derivatives for Trading
Interest Rate Derivatives for Hedging
Interest Rate Derivatives for Trading
Interest Rate Derivatives for Hedging
Panel E
Stress-Tested Banks
Average Interest Derivatives Use
Interest Rate Derivatives Traded OTC
Interest Rate Derivatives Traded in Exchange
Interest Rate Derivatives Traded OTC
Interest Rate Derivatives Traded in Exchange
Panel F
Stress-Tested Banks
Average Net Credit Derivatives Use
Net Credit Derivative

interest rate derivatives traded in the OTC market and in exchanges. Panel C and Panel F depict the average net credit derivatives holdings.

As presented in Figure 3.1, banks use a greater proportion of interest rate derivatives for trading than for hedging, and most of the interest rate derivatives were traded in the OTC market. From mid-to-end 2011 onwards, interest rate derivatives held for trading and interest rate derivatives traded in the OTC market declined, while interest rate derivatives in the exchanges increased, particularly for the main sample. Credit derivatives holdings increased substantially during 2007–2008 but were markedly lower as of 2009; the trend is more pronounced for stress-tested banks.

On average, a stress-tested bank holds substantially larger derivatives positions than a typical bank in the main sample. Stress-tested banks' interest rate derivatives held for trading and derivatives traded in the OTC increased sharply in the last two quarters of 2008 and leveled off afterwards.

The statistics of the dependent variables and key independent variables are presented in Panel A and Panel B of Table 3.1, respectively.

Due to the data availability of 157 banks in the main sample, the sample used for systemic risk analysis includes 3591 quarter-bank observations, while the sample used for bank-risk and bank-performance analysis includes 3905 quarter-bank observations. As presented in Panel A of Table 3.1, on average, a bank in the main sample has a *⊿CoVaR* of -2.8 percent, marginal expected shortfall (*MES*) of -3.5 percent, and an industry beta of 0.8 (benchmarked against S&P Banks Selected Industry Index). *⊿CoVaR* varies between -19.4 and 7.3 percent, while *MES* spreads over a wider range between -26.3 percent and 16.3 percent.

Table 3. 1 Summary Statistics

Panel A

Dependent Variables	Obs	Mean	Median	SD	Min	Max
△CoVaR	3591	-0.0277	-0.0228	0.0214	-0.1942	0.0726
MES	3591	-0.0346	-0.0262	0.0332	-0.2626	0.2407
Banking industry beta	3591	0.7834	0.8172	0.3065	0.0016	1.9287
Z-score	3905	3.4515	2.0772	4.3089	-1.0847	32.5934
Distance to default	3905	2.9638	2.7284	1.6649	0.0485	14.6817
Volatility	3905	0.0274	0.0213	0.0182	0.0052	0.2364
Tobin's Q	3905	1.0418	1.0094	0.2546	0.4371	4.1912
ROA	3905	0.0064	0.0087	0.0147	-0.1511	0.1779
Cost to income	3905	0.6749	0.6468	0.2293	0.2500	3.9750

This table presents the statistics of the variables calculated from the 157 banks in the sample using quarterly data from 2007Q1 to 2014Q4. Statistics of the dependent variables are presented in Panel A. *△CoVaR* is the difference between *Value at Risk* of the banking system conditional on the distress of a bank and *Value at Risk* of the banking system conditional on the median state of the bank. *MES* is a bank's marginal expected shortfall calculated as the average return of a bank on days when the S&P Banks Selected Industry Index return is among its lowest 5 percent level. *Banking industry beta* is calculated as the sensitivity of stock return to the return of the banking industry index in a one-year time window. The *Z-score* is the sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets. *Distance to default* is defined as the market value of total assets minus the sum of short-term debt and half of the long-term debt, then divided by the volatility of the market value of assets. *Tobin's Q* is defined as the market value of a bank's assets over the book value of assets. *ROA is the* return on assets defined as the ratio of net income to book value of total assets. *Cost to Income* is the ratio of operating cost to net interest income, which measures banks' operating efficiency.

Table 3.1 Summary Statistics (Cont'd)

Panel B

Key Independent Variables	Obs	Mean	Median	SD	Min	Max
IRDs trading	3905	0.4623	0.0000	3.2666	0.0000	51.1553
IRDs hedging	3905	0.0457	0.0105	0.1039	0.0000	1.5314
Net CDs	3905	0.0002	0.0000	0.0057	-0.0640	0.1217
IRDs OTC	3905	0.4125	0.0112	2.7447	-0.0329	42.3556
IRDs Exchange	3905	0.0184	0.0000	0.1028	-0.0359	1.4426
Loan to depository institutions	3591	0.1594	0.0000	1.0737	0.0000	20.6614
Balance due from depository institutions	3591	0.0096	0.0000	0.0521	-0.0208	1.0346
Size	3905	8.7597	8.3724	1.4868	6.5965	14.7603
Loan loss provision	3905	0.1991	0.0900	0.3382	-0.6409	4.9213
Tier 1 ratio	3905	0.0929	0.0914	0.0193	0.0313	0.1937
Exposure to housing price change	3905	-0.0016	-0.0017	0.0238	-0.0989	0.0849
HHI index	3905	6.5697	6.6127	0.5251	3.4417	8.0995

Statistics of the key explanatory variables are presented in Panel B. *IRDs trading* is defined as the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivatives sold OTC, then scaled by asset. *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchanges scaled by asset. *Size* is calculated as the logarithm of total assets. *Loan to depository institutions* is the ratio of Loan to depository institutions to total loans and leases in percentage. *Balance due from depository institutions* is the ratio of *Balance due from depository institutions* to total loans and leases in percentage. *Loan loss provision* is the ratio of loan loss provision to net interest income. *Tier 1 ratio* is tier 1 capital as a percentage of total risk-weighted assets. *Exposure to housing price change* is calculated as average weighted housing price changes derived by using the proportion of deposits a bank has in each state. *HHI index* is the logarithm value of the average weighted *Herfindahl-Hirschman Index* derived by using the proportion of deposits a bank has in each state.

Table 3.1 Summary Statistics (Cont'd)

Panel C

Dependent variables	Mean			Median		
	Pre-DFA	Post-DFA	Difference	Pre-DFA	Post-DFA	Difference
△CoVaR	-0.0339	-0.0226	0.0113***	-0.0291	-0.0192	0.0099***
MES	-0.0455	-0.0258	0.0197***	-0.0366	-0.0230	0.0136***
Banking industry beta	0.7595	0.8028	0.0433***	0.7548	0.8459	0.0911***
Z-score	3.9934	3.0566	-0.9368***	2.6408	1.6154	-1.0253***
Distance to default	2.0864	3.6032	1.5169***	1.8610	3.6381	1.7771***
Volatility	0.0374	0.0201	-0.0173***	0.0318	0.0163	-0.0155***
Tobin's Q	1.0033	1.0698	0.0664 ***	0.9862	1.0284	0.0422***
ROA	0.0035	0.0084	0.0050***	0.0071	0.0093	0.0022***
Cost to income	0.6846	0.6678	-0.0169**	0.6385	0.6544	0.0159***

Panel D

Derivatives use by banks	Mean			Median		
	Pre-DFA	Post-DFA	Difference	Pre-DFA	Post-DFA	Difference
IRDs trading	0.6216	0.3463	-0.2753***	0.0000	0.0121	0.0121
IRDs hedging	0.0477	0.0443	-0.0034	0.0077	0.0000	-0.0077***
Net CDs	0.0006	-0.0001	-0.0007***	0.0000	0.0146	0.0146
IRDs OTC	0.5393	0.3201	-0.2192***	0.0062	0.0000	-0.0062***
IRDs Exchange	0.0218	0.0160	-0.0059**	0.0000	0.0000	0.0000

Table 3.1 Panel C presents the mean and median of all dependent variables in Pre-DFA and Post-DFA periods respectively. Panel D presents the mean and median of derivatives use in Pre-DFA and Post-DFA periods. *△CoVaR* is the difference between *Value at Risk* of the banking system conditional on the distress of a bank and *Value at Risk* of the banking system conditional on the median state of the bank. *MES* is a bank's marginal expected shortfall calculated as the average return of a bank on days when the S&P Banks Selected Industry Index return is among its lowest 5 percent level. *Banking industry beta* is calculated as the sensitivity of stock return to the return of the banking industry index in a one-year time window. The *Z-score* is the sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets. *Distance to default* is defined as the market value of total assets minus the sum of short-term debt and half of the long-term debt, then divided by the volatility of the market value of assets. *Tobin's Q* is defined as the market value of a bank's assets over the book value of assets. *ROA is the* return on assets defined as the ratio of net income to book value of total assets. *Cost to Income* is the ratio of operating cost to net interest income, which measures banks' operating efficiency. *IRDs trading* is defined as the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivatives sold OTC, then scaled by asset. *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchanges scaled by asset.

In terms of banks' risk and bank performance, a typical bank, on average, has a *Z-score* of 3.5, *Distance to Default* of 2.96, *Volatility* of 2.74 percent, *return on assets* of 0.64 percent, *cost to income* of 0.67, and *Tobin's Q* of 1.04. These measures also vary widely. For example, *Z-score* ranges between -1.08 and 32.6, *Distance to Default* varies between 0.05 to 14.68, and *Tobin's Q* spreads over a larger range between 0.44 and 4.19. As shown in Table 3.1, Panel C, the means and medians of all dependent variables are statistically different in pre-DFA period and post-DFA period.

With regard to banks' derivatives use, it can be found in Panel B of Table 3.1 that the average interest rate derivatives holding for hedging and for trading (scaled by a bank's assets) are 4.6 percent and 46 percent, respectively. Derivatives held for trading vary markedly between 0 and 51.2 percent, while net credit derivatives spread between -6.4 and 12.2 percent. Panel D of Table 3.1 presents the mean and median of derivatives use by banks in pre- and post-DFA periods. It can be found that, overall, the average use of both interest rate derivatives and credit derivatives by banks declined after the signing of the DFA.

On average, a bank has an average size, calculated as the logarithm of its total asset, of 8.76, a *tier 1 risk capital ratio* of 9.29 percent, and *loan loss provision* of 19.9 percent. The average *loan to depository institutions* (scaled by *gross loans and leases*) is 0.16 percent, and the average *balance due from depository institutions* (scaled by *gross loans and leases*) is 0.01 percent.

3.5 Results

3.5.1 Derivatives, DFA, and systemic risk

I investigate (H3-1a), (H3-1b), and (H3-1c) with three measures of systemic risk: (1)*△CoVaR*, (2) *Marginal Expected Shortfall* (*MES*), and (3) *industry beta. △CoVaR* is the difference between the financial system's *VaR* conditional on bank *i'*s being in distress and the financial system's *VaR* in the median state of bank *i.* Bank *i'*s *MES* is its mean return on days when the S&P Banks Selected Industry Index return reaches its lowest 5 percent level over a quarter period. Bank *i*'s industry beta captures the sensitivity of its stock returns to the returns of the S&P Banks Selected Industry Index over a one-year period. Recall that *△CoVaR* and *MES* have negative mean and median values (see Panel A Table 3.1). A lower value (negative) of *△CoVaR* and *MES* and a higher *industry beta* indicate a higher marginal contribution by bank *i* to systemic risk.

Table 3.2 and Table 3.3 report the systemic regression results for Equation (3.4). Bank-quarter observations have both a time series and a cross-sectional dimension. I estimate Equation (3.4) as a panel regression and control for firm and time fixed effects. In each regression in Table 3.2, three measures of derivatives categorized by holding purposes (then scaled by a bank's assets) are employed, while each regression in Table 3.3 reports regressions with measures of derivatives categorized by trading approaches (then scaled by a bank's assets). In both Table 3.2 and Table 3.3, Columns (1), (2), and (3), respectively, show the effects of derivatives holdings, without considering the DFA, on *△CoVaR*, *MES,* and *industry beta*. Columns (4), (5), and (6), respectively, extend columns (1), (2), and (3); each features the dummy, *PostDFA,* and three interaction terms between derivative categories and *PostDFA*.

As shown in Table 3.2, interest rate derivatives holdings for hedging (*IRDs hedging*) is significant in every estimated model. Its negative (positive) coefficients in columns (1), (2), (and (3)), when *△CoVaR* and *MES* (*industry beta*) were used to capture systemic risk indicate that its use results in a larger contribution to systemic risk. This finding is consistent with hypothesis (H3-1a) that banks' holdings of derivatives increased their contribution to systemic risk.

IRDs trading is marginally significant when *△CoVaR* is the dependent variable (column (1)), suggesting that interest rate derivatives for trading by banks also increases systemic risk. However, its effect is much smaller compared with the effect of *IRDs hedging*. *IRDs trading* becomes insignificant when *PostDFA* is added to the models.

Table 3. 2 Effects of Derivatives Use and DFA on Systemic Risk

	(1) △CoVaR	(2) MES	(3) Bank beta	(4) △CoVaR	(5) MES	(6) Bank beta
IRDs trading	-0.0003*	-0.0001	0.0045	-0.0001	0.0001	0.0042
IRDs hedging	-0.0112*	-0.0108*	0.2138***	-0.0148***	-0.0188**	0.2201***
Net CDs	-0.0638	-0.1220*	0.6413	-0.2040***	-0.2476***	1.5666*
Loan to depository institutions	0.1178	0.2701	0.5246	0.0920	0.2145	0.3651
Balance due from depository institutions	0.6975**	-1.1726*	2.3435	0.7721***	-1.1318**	1.4668
Post DFA dummy				0.0075***	-0.0136***	-0.2212***
IRDs trading* PostDFA				-0.0001	-0.0004*	0.0038
IRDs hedging * PostDFA				0.0117***	0.0307***	-0.0823
Net CDs * PostDFA				0.4789***	0.3290***	-2.6399
Size	0.0004	-0.0060**	0.2099***	0.0003	-0.0061**	0.2099***
Tier 1 ratio	-0.0187	-0.0469	1.6703***	-0.0200	-0.0504	1.6812***
Loan Loss Provision	-0.0021***	-0.0060***	0.0132	-0.0019***	-0.0057***	0.0129
Book-to-market ratio	-0.0001	0.0022**	-0.0338***	-0.0001	0.0021**	-0.0338***
Return on average assets	-0.0162	-0.0027	0.2777	-0.0145	0.0006	0.2750
Short-term borrowing	-0.0849***	-0.0758**	-0.1397	-0.0815***	-0.0667**	-0.1382
Stock volatility	-0.1338***	-0.3969***	8.8313***	-0.1227***	-0.3787***	8.7930***
Acquisition	0.0007	-0.0002	-0.0425***	0.0007	-0.0004	-0.0421***
Special capital users dummy	-0.0009	-0.0007	-0.0008	-0.0007	-0.0004	-0.0014
Exposure to housing price change	0.0076	0.0719**	-0.1422	0.0062	0.0698**	-0.1354
HHI index	0.0015	0.0041	0.0022	0.0011	0.0039	0.0011
Intercept	-0.0352	0.0242	-1.0321**	-0.0318	0.0275	-1.0256**
Adj.R-squared	0.626	0.610	0.405	0.630	0.612	0.406
N	3591	3591	3591	3591	3591	3591

The dependent variables in the regressions are change in conditional Value at Risk at 95 percent (*△CoVaR*), marginal expected shortfall at 95 percent (*MES*) and banking industry beta (*Bank beta*) calculated using one year of daily stock price. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivatives sold, then scaled by asset. *Loan to depository institutions* is the ratio of Loan to depository institutions to total loans and leases. *Balance due from depository institutions* is the ratio of *Balance due from depository institutions* to total loans and leases. *PostDFA* is a dummy set to one after the Dodd-Frank Act is singed and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Without considering the DFA, *Net CDs* is marginally significant in column (2) when *MES* is employed to capture systemic risk. However, it is significant in columns (4), (5) and (6) which feature *PostDFA* and the interaction terms. Consistent with hypothesis (H3-1a), these results indicate that the use of credit derivatives raises banks' contribution to systemic risk without considering the effects of the DFA. It can be also noticed that the effects of credit derivatives (*Net CDs*) on banks' contribution to systemic risk are stronger than those of interest rate derivatives (*IRDs trading* and IRDs *hedging*) without considering the effects of the DFA.

Overall, interest rate derivatives held for hedging are the only category which is significant in every estimated model. Net credit derivatives (*Net CDs*) exhibit the significant effect when the DFA and interaction terms are included. Interest rate derivatives held for trading show the weakest impact on systemic risk. The effects of significant derivatives variables are consistent with hypothesis (H3-1a) that derivatives use raises banks' contribution to systemic risk without considering the effects of the DFA and in line with the findings of Calmes and Theoret (2010) and Nijskens and Wagner (2010) that banks' use of derivatives led to higher systemic risk.

PostDFA represents the period after the DFA came into effect. It is significant in all three columns (4), (5), and (6). However, the coefficient of *PostDFA* flips sign when *MES* is the dependent variable (column (5)). None of columns (4), (5), and (6) features all three significant interaction terms between derivatives holdings and *PostDFA.* The two interaction terms between *Net CDs, IRDs hedging,* and *PostDFA* are significant when *△CoVaR* and *MES* are used to capture systemic risk. The positive coefficient signs in columns (4) and (5) support hypothesis (H3-1c) that the implementation of the DFA reduces, even reversed, the exacerbating effects of these derivatives on systemic risk, although the interaction terms between *IRDs trading* and *PostDFA* feature no significant coefficients in column (4). The results on interest rate derivatives for hedging are consistent with Li and Marinč (2017), while the findings on credit derivatives and the DFA show contrary results. Then I employ all the estimated coefficients and means of all independent variables to predict the level of systemic risk measures in pre- and post-DFA periods. I document that the estimated *△CoVaR* increased from -0.033 to -0.019, estimated *MES* increased from -0.036 to -0.024, and *Bank beta* decreased from 0.988 to 0.841. These findings are consistent with hypothesis (H3-1b) that the implementation of the DFA lowers banks' contribution to systemic risk caused by derivatives.

Overall, the results in Table 3.2 confirm hypotheses (H3-1a) and (H3-1c) for two out of the three derivatives categories examined (credit derivatives and interest rate derivatives for hedging) and partly support hypothesis (H3-1b). However, the insignificant results on *IRDs trading* as well as the interaction terms between *IRDs trading* and *PostDFA* did not provide supportive evidence for the effectiveness of the proprietary trading approach by the Volcker Rule of the DFA.

In addition to the three derivatives variables discussed above, *loan to depositary institutions* and *balances due from depository institutions* also capture the extent of interconnectedness among banks. *Loan to depositary institutions* is not significant in any of the models, which is consistent with Mayordomo, Rodriguez-Moreno, and Pena (2014), while *balances due from depository institutions* is significant in four out of six columns (columns (1), (2), (4), and (5)). However, the coefficient sign in columns (1) and (4) is not consistent with the coefficient sign in columns (2) and (5). If *MES* is a more relevant measure than *△CoVaR* to capture systemic risk, then its negative sign in columns (2) and (5) suggests a higher degree of systemic risk.

Adding *PostDFA* and the interaction terms in columns (4), (5), and (6) in Table 3.2 does not change the significance of any control variables (compared with columns (1), (2), and (3)). The *volatility* of stock returns is the only variable which is significant in every model in Table 3.2. *Short-term borrowing* and *loan loss provision* are significant in four out of six models (columns (1), (2), (4), and (5)). As expected, the negative sign of the coefficients of these three variables, when significant, indicates that a higher degree of uncertainty, insufficient liquid assets, and poor asset quality increase systemic risk. Bank *size* is significant in four out of six models (columns (2), (3), (5), and (6)). *Book-to-market ratio, Tier 1 risk ratio,* and the dummy *acquisition* are significant in columns (3) and (6). The results suggest that large banks, healthier banks (higher *Tier 1 risk ratio*), or those with a small *book-to-market ratio* are more likely to do business with a number of financial institutions and thereby raise systemic risk. The coefficient of *exposure to housing price change* is significant and positive in columns (2) and (5). Considering that both the mean and median of *exposure to housing price change* are negative, its positive coefficient suggests, on average, high exposure to the real estate market increases systemic risk. In contrast, *acquisitions* is found to diminish banks' systemic risk, but only when Bank Beta is employed in columns (3) and (6).

Table 3.3 presents the results with derivatives categorized by trading approaches of OTC or on exchanges. As shown in Table 3.3, without considering the DFA, interest rate derivatives traded on exchanges (*IRDs exchange*) is significant when industry beta is used to capture systemic risk (model 3). It is significant in columns (4) and (6) when *PostDFA* and the interaction terms were added. Its negative (positive) coefficients when *△CoVaR* (*industry beta*) were used to capture systemic risk indicate that derivatives traded on exchanges result in a larger contribution to systemic risk. This finding is consistent with hypothesis (H3-1a) that derivatives use by banks increase their contribution to systemic risk. On the other hand, none of the models in Table 3.3 features significance for the coefficient of *IRDs OTC*.

Net CDs is significant in columns (4), (5) and (6) in Table 3.3, where the *PostDFA* dummy and interaction terms are added. In addition, *Net CDs* shows marginal significance in column (2). Its negative coefficient sign in columns (4), (5) and positive coefficient sign in column (6) suggests that the use of OTC-traded credit derivatives raises banks' contribution to systemic risk without considering the effects of the DFA, which is consistent with the findings in Table 3.2 and hypothesis (H3-1a) about the positive effect of derivatives use on banks' contribution to systemic risk.

Overall, in the presence of *PostDFA* and the respective interaction terms, interest rate derivatives traded on exchanges (*IRDs exchange*) significantly increase banks' contribution to systemic risk without considering the effects of the DFA, while interest rate derivatives traded OTC (*IRDs OTC*) presents insignificant effects. Credit derivatives traded OTC (*Net CDs*) are found to raise systemic risk without considering the effects of the DFA, and such effects are reversed in post-DFA period.

As shown in Table 3.3, the interaction term between *IRDs OTC* and *PostDFA* is marginally significant only when *industry beta* is used to capture systemic risk (column (6)). The positive coefficient sign, however, suggests that after the implementation of the DFA, *IRDs OTC* marginally increases systemic risk, which is contrary to hypothesis (H3-1c) that the DFA limited the impacts of derivatives on banks' contribution to systemic risk. The interaction term between *IRDs exchange* and *PostDFA* is also marginally significant in column (6) but with a negative sign, which suggests that the implementation of the DFA marginally mitigated the exacerbating effect of interest rate derivatives traded on exchanges on systemic risk. The two interaction terms between *Net CDs* and *PostDFA* are significant when *△CoVaR* and *MES* are used to capture systemic risk. The positive signs in columns (4) and (5) together with relatively greater coefficient magnitudes suggest that the DFA reversed the negative effects of credit derivatives on banks' systemic risk, which support hypothesis (H3-1c) that the implementation of the DFA reduces the exacerbating effects of credit derivatives traded OTC on systemic risk.

Table 3. 3 Effects of Derivatives Use and DFA on Systemic Risk

	(1) △CoVaR	(2) MES	(3) Bank beta	(4) △CoVaR	(5) MES	(6) Bank beta
IRDs OTC	-0.0003	0.0001	0.0036	-0.0001	0.0002	0.0075
IRDs exchange	-0.0140	-0.0123	0.1994**	-0.0223**	-0.0187	0.2757**
Net CDs	-0.0671	-0.1340*	0.7402	-0.1803***	-0.2152***	1.1545**
Loan to depository institutions	0.1353	0.2853	0.2150	0.1224	0.2738	-0.0052
Balance due from depository institutions	0.7257*	-1.1374*	1.7687	0.8241**	-1.0674	0.6571
Post DFA dummy				0.0078***	-0.0124***	-0.2223***
IRDs OTC * PostDFA				-0.0005	-0.0004	0.0133*
IRDs exchange * PostDFA				0.0091	0.0070	-0.1783*
Net CDs * PostDFA				0.4456***	0.3231***	-1.6348
Size	0.0003	-0.0060**	0.2101***	0.0003	-0.0060**	0.2081***
Tier 1 ratio	-0.0184	-0.0468	1.6582***	-0.0191	-0.0473	1.6671***
Loan Loss Provision	-0.0021***	-0.0060***	0.0133	-0.0020***	-0.0059***	0.0141
Book-to-market ratio	-0.0000	0.0022**	-0.0343***	-0.0001	0.0022**	-0.0346***
Return on average assets	-0.0153	-0.0019	0.2607	-0.0147	-0.0015	0.2719
Short-term borrowing	-0.0869***	-0.0774**	-0.1029	-0.0875***	-0.0777**	-0.0603
Stock volatility	-0.1364***	-0.3996***	8.8784***	-0.1304***	-0.3951***	8.8677***
Acquisition	0.0009	-0.0000	-0.0463***	0.0010	0.0000	-0.0461***
Special capital users dummy	-0.0009	-0.0007	-0.0010	-0.0008	-0.0006	-0.0007
Exposure to housing price change	0.0065	0.0708**	-0.1241	0.0058	0.0703**	-0.1312
HHI index	0.0017	0.0043	-0.0007	0.0013	0.0039	-0.0022
Intercept	-0.0362	0.0234	-1.0075**	-0.0332	0.0257	-0.9841**
Adj.R-squared	0.625	0.610	0.402	0.628	0.610	0.404
N	3591	3591	3591	3591	3591	3591

The dependent variables in the regressions are change in conditional Value at Risk at 95 percent (*△CoVaR*), marginal expected shortfall at 95 percent (*MES*), and banking industry beta (*Bank beta*) calculated using one year of daily stock price. *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchange scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *Loan to depository institutions* is the ratio of Loan to depository institutions to total loans and leases. *Balance due from depository institutions* is the ratio of *Balance due from depository institutions* to total loans and leases. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Overall, the results on interest rate derivatives traded on exchanges, credit derivatives (traded OTC), and their interaction terms in Table 3.3 confirm hypothesis (H3-1a), and (H3-1c), while the results on interest rate derivatives traded OTC show they have insignificant impacts on systemic risk without considering the effects of the DFA. However, the interaction term between *IRDs OTC* and *PostDFA* indicates that after the signing of the DFA, interest rate derivatives traded OTC (*IRDs OTC*) marginally increased systemic risk when *industry beta* in used to capture systemic risk. The findings on *Net CDs* provide supportive evidence that the central clearing channel of the DFA effectively lowered banks' systemic risk associated with credit derivatives traded OTC. On the other hand, the findings on *IRDs OTC* suggest that the central clearing channel of the DFA did not work out appropriately for interest rate derivatives traded OTC. All the other control variables in Table 3.3 present consistent significance and signs as in Table 3.2.

As previously discussed in Section 3.3.1, to deal with potential bias caused by using the *CoVaR* as the measure of contribution to systemic risk, I also run regressions within a subsample of big banks. By doing this, it allows to eliminate the bias caused by same banks that have similar return correlation to the banking sector like big banks. I document consistent results that banks' use of interest rate derivatives for hedging (*IRDs hedging*), traded on exchanged (*IRDs exchange*), and credit derivatives (*Net CDs*) increased their contribution to systemic risk without considering the effects of the DFA; the DFA effectively mitigated, even reversed, the impacts of these derivatives on banks' systemic risk.[52]

3.5.2 Derivatives, DFA, and banks' risk

I investigate (H3-2a), (H3-2b), (H3-2c), and (H3-3) with three measures of bank risk: (1) *Z-score*, as calculated by Laeven and Levine (2009); (2) *distance to default*; (3) stock *volatility*. *Z-score*, calculated by using the data of the past 16 quarters, and

[52] The result table for big banks is presented in Appendix 3.3, Panel A. Details of the results are discussed in Section 3.6.1.

distance to default capture banks' credit risk. *Volatility* of stock return captures banks' overall risk and is calculated by using six-month daily stock return data.

Table 3.4 and Table 3.5 report the regression results for Equation (3.8). Columns (1), (2), and (3) respectively, show the effects of derivatives categories, without considering the DFA, on *Z-score*, *distance to default,* and *stock volatility*. Columns (4), (5), and (6), respectively, extend columns (1), (2), (3) by adding *PostDFA* and three interaction terms between three derivatives categories and *PostDFA*.

As shown in Table 3.4, without considering the DFA, *Net CDs* is significant in column (1) and column (3). The negative sign of the *Net CDs'* coefficient in column (1) suggests that the use of credit derivatives lowers banks' *Z-score* and raises banks' credit risk. Consistently, the positive sign of the *Net CDs'* coefficient in column (3) suggests the use of credit derivatives increases banks' overall risk. These findings are consistent with hypothesis (H3-2b) that credit derivatives increase banks' risk and in line with Keppo and Korte (2016). *IRDs trading* is significant in columns (3) and (6) with a negative sign. Considering the insignificant coefficient of its interaction with *PostDFA* in column (6), this finding suggests that the use of interest rate derivatives for trading lowers banks' stock volatility and does not support hypothesis (H3-2a) that both *IRDs* used for trading and hedging increased banks' risk.

Table 3. 4 Effects of Derivatives Use and DFA on Banks' Risk

	(1) Z-score	(2) Distance to Default	(3) Volatility	(4) Z-score	(5) Distance to Default	(6) Volatility
IRDs trading	-0.0534	0.0018	-0.0002*	-0.0563	0.0048	-0.0004***
IRDs hedging	-0.9677	-0.2788	0.0029	-0.9115	-0.1977	0.0069**
Net CDs	-16.7251**	-7.8770	0.0937***	-12.6877	-16.1080***	0.1527***
PostDFA				-6.3159***	-3.2599***	0.0191***
IRDs trading * PostDFA				0.0145	-0.0346***	-0.0000
IRDs hedging * PostDFA				-0.4083	0.2864	-0.0121**
Net CDs * PostDFA				-11.9843	24.7365***	-0.2108***
Size	0.7190	0.6475***	-0.0039**	0.7195	0.6501***	-0.0037**
Tier 1 ratio	-12.4058*	5.3142**	-0.1281***	-12.3644*	5.2740**	-0.1259***
Loan Loss Provision	-0.0815	-0.1855***	0.0046***	-0.0830	-0.1889***	0.0044***
Book-to-market ratio	0.0445	0.0927*	0.0065***	0.0442	0.0950*	0.0065***
Return on assets			-0.0270*			-0.0292**
Short-term borrowing	9.7799**	-3.6256**	0.0303***	9.7641**	-3.8473**	0.0255**
Stock volatility 6ms	-9.0371	-20.0225***		-9.2334	-19.8870***	
Acquisition	-0.3102	-0.0289	-0.0003	-0.3086	-0.0274	-0.0002
Special capital users dummy	-0.0008	-0.0176	0.0010**	-0.0038	-0.0170	0.0008*
Exposure to housing price change	-6.0749	-1.3222	-0.0195	-6.0373	-1.3522	-0.0180
HHI index	0.3232	-0.1134	0.0003	0.3228	-0.0983	0.0006
Intercept	0.9926	0.8133	0.0517***	0.9879	0.6907	0.0476***
Adj.R-squared	0.388	0.589	0.824	0.388	0.590	0.826
N	3905	3905	3905	3905	3905	3905

The dependent variables in the regressions are *Z-score, distance to default*, and six-month stock price *volatility*. For brevity reasons, time fixed effects and firm fixed effects are not reported. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

As *PostDFA* and the three interaction terms are added in column (4), (5), and (6) in Table 3.4, *Net CDs* is significantly negative (positive) in column (5) (column (6)), suggesting the use of credit derivatives lowers (increases) banks' *distance to default* (*stock volatility*) and therefore increase banks' credit risk (overall risk) without considering the effects of the DFA. *IRDs hedging* is only significant in column (6). The positive coefficient sign of *IRDs hedging* in column (6) suggests that holdings of interest rate derivatives for hedging lead to higher banks' overall risk, as measured by *stock volatility* without considering the effects of the DFA. This result is in line with Deng, Elyasiani, and Mao (2017), Ghosh (2017), Titova, Penikas, and Gomayun (2018) and can be explained by the fact that banks are likely to hedge risk just in order to take more risks and earn higher economic rents.

In Table 3.4, the interaction term between *IRDs hedging* and *PostDFA* is significant in column (6). Its negative coefficient sign with a greater magnitude indicates that the signing of the DFA reversed the exacerbating effects of interest rate derivatives for hedging on banks' volatility. The interaction term between *IRDs trading* and *PostDFA* is significant in column (5), and the negative coefficient sign suggests that after the implementation of the DFA, banks' use of interest rate derivatives for trading induced higher credit risk, as measured by *distance to default*. The interaction term between *Net CDs* and *PostDFA* is significant in columns (5) and (6), and the magnitudes of the coefficients for credit derivatives and its interaction term with *PostDFA* are found to be much larger than those of the coefficients of *Net CDs*. These findings indicate that implementation of the DFA reversed the effects of credit derivatives on banks' risk.

PostDFA is significant in all three models in Table 3.4 (columns (4), (5) and (6)). It shows significantly negative coefficient in columns (4) and (5) and significantly positive coefficient in column (6). In order to test hypothesis (H3-3), again, I predict the mean level of banks' risks in the pre- and post-DFA periods by using estimated coefficients of all independent variables together with their means. I found that lower estimated *Z-score*, with higher *Distance to Default* and lower *Volatility* after the commencement of the DFA. These mixed results cannot confirm hypothesis (H3-3) that the DFA increased banks' risks; only the findings with *Z-score* is in line with Chung, Keppo, and Yuan (2016). Overall, the empirical evidence in Table 3.4 is consistent with hypothesis (H3-2b). The results on *IRDs trading* do not support hypothesis (H3-2a).

Adding *PostDFA* and the interaction terms in columns (4), (5), and (6) in Table 3.4 does not change the significance of any control variables (compared with columns (1), (2), and (3)). Table 3.4 features only two significant control variables in all models, namely, *tier 1 ratio* and *short-term borrowing.* However, for both variables, the coefficient sign in columns (1) and (4) is not consistent with the findings in other models. Results in columns (2), (3), (5), and (6) suggest that *short-term borrowing* increased banks' credit risk and overall risk as measured by *distance to default* and *stock volatility,* respectively. The coefficient of *tier 1 ratio* in columns (2), (3), (5), and (6) suggest that banks with higher *tier 1* ratio are likely to experience lower credit and overall risk. *Loan loss provisions* is significant in columns (2), (3), (5), and (6). Its negative coefficient sign in columns (2) and (5) and positive sign in columns (3) and (6) suggests that banks with poor asset quality (*loan loss provisions*) tend to experience higher credit risk, and overall risk. *Book-to-market ratio* is found statistically significant and positive in column (2), (3), (5) and (6), which indicates that banks with higher *book-to-market ratio* are likely to have lower credit risk (*distance to default*) but higher overall risk (*stock volatility*). The significantly negative coefficient sign of *stock volatility* in columns (2) and (5) indicates that banks with higher stock returns *volatility* are likely to get higher credit risk. *Return on assets* and the *special capital program* dummy are significant only in columns (3) and (6) when stock volatility is used to capture banks' risk. Banks which achieve lower profitability (*return on assets*) and those which use one of the special capital programs or the discount window borrowing show more volatility and higher overall risk. Total assets (*size*) is significant in (2), (3), (5) and (6). Large banks exhibit lower credit risk measured by *distance to default*, and show a lower degree of volatility in their stock returns. *Exposures to real estate market* is not significant in any model.

Table 3.5 presents the results on banks' risk with derivatives categorized by trading approach of OTC and exchanges. Without considering the DFA, *IRDs OTC* is significant in column (3) with a negative coefficient sign, which suggests banks with more *IRDs OTC* exhibit lower stock volatility and overall risk. *IRDs exchange* is significant in column (2), and its negative coefficient sign indicates that the use of exchange-traded interest rate derivatives increases banks' credit risk (proxied by lower *distance to default*). The findings on interest rate derivatives provide evidence against hypothesis (H3-2c) that OTC derivatives increased banks' risk. *Net CDs* is significantly negative in columns (1), (2) and significantly positive in column (3), suggesting that banks' use of credit derivatives traded OTC raises credit risk (lower *Z-score* and *distance to default*) and overall risk (higher *volatility*). These findings on credit derivatives support hypothesis (H3-2c) that derivatives trade OTC raised banks' risk.

Adding *PostDFA* and the three interaction terms in Table 3.5 does not change the significance and sign for *IRDs OTC* and *Net CDs*, while *IRDs exchange* becomes significant in column (6). The positive sign in column (6) show that the use of interest rate derivatives traded on exchanges increases banks' overall risk taking into account that its interaction term is insignificant in column (6). The *PostDFA* dummy is significant in all three models in Table 3.5 (columns (4), (5), and (6)). These predicted results for pre- and post-DFA periods with estimated coefficients of all independent variables, again, do not entirely support hypothesis (H3-3) that the implementation of the DFA increased banks' risk.

Table 3. 5 Effects of Derivatives Use and DFA on Banks' Risk

	(1) Z-score	(2) Distance to Default	(3) Volatility	(4) Z-score	(5) Distance to Default	(6) Volatility
IRDs OTC	-0.0122	0.0104	-0.0003**	-0.0504	0.0275	-0.0004***
IRDs exchange	-0.4084	-0.7197**	0.0013	-1.1612	-0.3656	0.0074*
Net CDs	-20.4831**	-8.0379*	0.0951***	-13.7031	-17.6023***	0.1294***
Post DFA dummy				-6.3530***	-3.2405***	0.0187***
IRDs OTC * PostDFA				-0.0724	-0.0046	0.0001
IRDs exchange * PostDFA				1.4775	-0.4775	-0.0055
Net CDs * PostDFA				-19.6428	29.6189***	-0.1878***
Size	0.7281	0.6409***	-0.0039**	0.7355	0.6402***	-0.0037**
Tier 1 ratio	-12.3608*	5.3009**	-0.1285***	-12.3524*	5.2716**	-0.1279***
Loan Loss Provision	-0.0898	-0.1855***	0.0046***	-0.0902	-0.1892***	0.0045***
Book-to-market ratio	0.0492	0.0932*	0.0065***	0.0492	0.0947*	0.0065***
Return on average assets			-0.0271*			-0.0283*
Short-term borrowing	9.6578**	-3.7033**	0.0309***	9.6502**	-3.9309**	0.0299***
Stock volatility	-9.2273	-20.1708***		-9.1606	-20.1036***	
Acquisition	-0.2977	-0.0225	-0.0004	-0.2995	-0.0207	-0.0004
Special capital users dummy	-0.0011	-0.0199	0.0010**	-0.0010	-0.0199	0.0009*
Exposure to housing price change	-6.0831	-1.3452	-0.0195	-6.0387	-1.3665	-0.0190
HHI index	0.3382	-0.1086	0.0002	0.3307	-0.0980	0.0006
Intercept	0.7551	0.8416	0.0522***	0.7749	0.7654	0.0482***
Adj.R-squared	0.388	0.589	0.824	0.388	0.590	0.825
N	3905	3905	3905	3905	3905	3905

The dependent variables in the regressions are *Z-score, distance to default*, and six-month stock price *volatility*. *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchange scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

As shown in Table 3.5, the interaction term between *IRDs OTC* and *PostDFA* and that between *IRDs exchange* and *PostDFA* are not significant. The interaction term between *Net CDs* and *PostDFA* is significant in columns (5), and (6). Its positive coefficient sign in (5) and negative coefficient sign in (6) with relatively higher magnitudes suggest that the signing of the DFA reversed the exacerbating effects of credit derivatives traded OTC on banks' risk.

Overall, the empirical evidence from credit derivatives (traded OTC) in Table 3.5 are consistent with hypothesis (H3-2c). On the other hand, the findings on the interaction term between interest rate derivatives traded OTC and *PostDFA,* and the interaction between interest rate derivatives traded on exchange and *PostDFA* do not support (H3-2c). Other control variables are found with consistent significance and signs as in Table 3.4.

3.5.3 Derivatives, DFA, and banks' performance

I investigate (H3-4), and (H3-5) with *Tobin's Q, return on asset,* and *cost-to-income ratio*. Table 3.6 and Table 3.7 report the regression results for Equation (3.9). Similarly, columns (1), (2), and (3) report the effects of derivatives holdings, without considering the DFA, and columns (4), (5), and (6) extend this by adding *PostDFA* and interaction terms between three derivative categories and *PostDFA* dummy.

Table 3. 6 Effects of Derivatives Use and DFA on Bank Performance

	(1) Tobin's Q	(2) ROA	(3) Cost to Income	(4) Tobin's Q	(5) ROA	(6) Cost to Income
IRDs trading	0.0061	0.0000	-0.0013	0.0038	-0.0000	0.0006
IRDs hedging	0.1633*	-0.0076	0.0760	0.1945***	-0.0067	0.0352
Net CDs	0.1004	0.0194	0.3066	0.0925	0.0111	0.4935
Post DFA				0.0068	0.0036	0.0174
IRDs trading * PostDFA				-0.0063**	-0.0001	0.0060***
IRDs hedging * PostDFA				0.0100	-0.0007	0.0271
Net CDs * PostDFA				-1.2917	0.0083	0.4277
Size	0.0092	-0.0084***	-0.0447**	0.0112	-0.0083***	-0.0466**
Tier 1 ratio	-0.8435	-0.0141	-0.1301	-0.8477	-0.0141	-0.1322
Loan Loss Provision	-0.0515***	-0.0079***	-0.0031	-0.0539***	-0.0079***	-0.0002
Book-to-market ratio		-0.0029***	0.0195*		-0.0029***	0.0187*
Return on average assets	0.2835		-0.8055	0.2558		-0.7755
Short-term borrowing	0.1375	0.0150	-0.3609	0.0848	0.0136	-0.2977
Stock volatility	-1.6565***	-0.0890*	1.9464***	-1.6923***	-0.0902*	2.0139***
Acquisition	0.0153	-0.0004	-0.0018	0.0150	-0.0004	-0.0019
Special capital users dummy	0.0098	-0.0002	-0.0140	0.0080	-0.0002	-0.0122
Exposure to housing price change	0.8195*	0.0992***	-0.9409**	0.8263**	0.0993***	-0.9508**
HHI index	-0.0016	0.0015	0.0113	0.0063	0.0016	0.0038
Intercept	1.2231*	0.0770***	0.9147***	1.1569*	0.0757***	0.9794***
Adj.R-squared	0.417	0.182	0.046	0.419	0.182	0.047
N	3905	3905	3905	3905	3905	3905

The dependent variables in the regressions are *Tobin's Q*, return on assets (*ROA*), and *cost to income*. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total asset. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

As shown in Table 3.6, without considering the DFA and interaction terms, only *IRDs hedging* is significant in column (1) when *Tobin's Q* is used to capture banks' performance. The positive coefficient sign suggests that the use of *IRDs hedging* improves banks' performance. As the *PostDFA* dummy and interaction terms were added in columns (4), (5), and (6), *IRDs hedging* still exhibits positive significance when *Tobin's Q* is used to capture banks' performance (column (4)) and confirms hypothesis (H3-4) that derivatives holdings improve banks' performance. *Net CDs* and *IRDs trading* are not found to be significant in any models in Table 3.6.

As noted in column (4) in Table 3.6, *o*f the three interaction terms included in columns (4), (5), and (6), the interaction term between *IRDs trading* and *PostDFA* is the only one that presents significance. The negative sign of this interaction term coefficient in columns (4) and the positive sign in column (6) suggest that after the signing of the DFA, the use of interest derivatives held for trading lowers banks' valuation (*Tobin's Q*) and operating efficiency (*cost to income*).

The results of other control variables suggest that large banks with poor asset quality (*loan loss provisions*), high *book-to-market ratio*, *stock volatility*, and low *short-term borrowings* tend to exhibit worse performance. The coefficient of *exposures to housing price change* is significantly positive in columns (2) and (5), and negative in columns (3) and (6). Considering its mean and median are both negative, these findings suggest that, on average, banks with higher *exposures to housing price change* tend to perform worse (lower *ROA* and higher *cost to income*) during the study period.

Table 3.7 presents results on banks' performance with derivatives categorized by trading approach of OTC and exchanges. Without considering the DFA, none of the *derivative* measures are significant. As shown in in Table 3.7, the interaction term between *IRDs OTC* and *PostDFA* is significant in columns (5) and (6), and the negative sign in column (5) with the positive sign in column (6) indicate that after the DFA came into effect, banks' use of interest rate derivatives traded OTC diminishes banks' performance (*ROA*) and operation efficiency (*cost-to-income ratio*). The interaction term between *IRDs exchanges* and *PostDFA* is significant in columns (4) and (6), and the negative sign suggests that the use of exchanged-traded interest rate derivatives in the post-DFA period improves banks' operational efficiency (proxied by lower *cost-to-income ratio*), but lowers banks' valuation (measured by lower *Tobin's Q*). Other control variables are consistent as in Table 3.6 in terms of significance and signs.

However, the predicted levels of banks' performance and efficiency, with estimated coefficients and means of independent variables in the pre- and post-DFA periods, show that banks' performance and efficiency were improved after the signing of the DFA(proxied by higher *Tobin's Q* and *RoA*; lower *Cost to Income*). These findings are against hypothesis (H3-5).

Table 3. 7 Effects of Derivatives Use and DFA on Bank Performance

	(1) Tobin's Q	(2) ROA	(3) Cost to Income	(4) Tobin's Q	(5) ROA	(6) Cost to Income
IRDs OTC	0.0027	0.0001	-0.0024	0.0031	0.0001	0.0042
IRDs exchange	0.1392	-0.0045	0.0538	0.3052	-0.0032	0.0564
Net CDs	0.3642	0.0122	0.3335	0.0454	-0.0002	0.1225
Post DFA dummy				0.0104	0.0035	0.0202
IRDs OTC * PostDFA				0.0036	-0.0003**	0.0145***
IRDs exchange * PostDFA				-0.1830**	0.0010	-0.1435***
Net CDs * PostDFA				-0.5897	0.0143	1.5835
Size	0.0087	-0.0083***	-0.0448**	0.0108	-0.0083***	-0.0482**
Tier 1 ratio	-0.8515	-0.0133	-0.1381	-0.8533	-0.0134	-0.1377
Loan Loss Provision	-0.0509***	-0.0079***	-0.0028	-0.0534***	-0.0080***	0.0001
Book-to-market ratio		-0.0029***	0.0192*		-0.0028***	0.0184*
Return on average assets	0.2794		-0.8085	0.2483		-0.7769
Short-term borrowing	0.1717	0.0134	-0.3435	0.1344	0.0118	-0.2870
Stock volatility	-1.6398***	-0.0908*	1.9651***	-1.6866***	-0.0915*	1.9995***
Acquisition	0.0126	-0.0002	-0.0032	0.0116	-0.0003	-0.0023
Special capital users dummy	0.0101	-0.0002	-0.0139	0.0082	-0.0003	-0.0124
Exposure to housing price change	0.8237*	0.0992***	-0.9403**	0.8304**	0.0994***	-0.9550**
HHI index	-0.0047	0.0016	0.0097	0.0038	0.0018	0.0033
Intercept	1.2549*	0.0754***	0.9291***	1.1784*	0.0737***	0.9948***
Adj.R-squared	0.415	0.181	0.046	0.418	0.181	0.048
N	3905	3905	3905	3905	3905	3905

The dependent variables in the regressions are *Tobin's Q*, return on assets (*ROA*), and *cost to income*. *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchange scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivative sold, then scaled by asset. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

3.6 Sensitivity Analysis

3.6.1 Sample of bigger banks

The main sample includes the BHCs with at least $1 billion in total assets as of year-end 2006. By doing so, I examined the effects of derivatives use by those banks that might become defunct during and after the GFC. In the first robustness test, following Mayordomo, Rodriguez-Moreno, and Pena (2014), I employ another sample with banks whose total assets were above $5 billion in the first quarter of 2006 and the first quarter of 2009. The subsample consists of 52 BHCs and allows to avoid potential bias, as it incorporates both pre-crisis and ongoing crisis-period time spots.

The robustness results are presented in Appendix 3.3 (Panel A to Panel I). For those 52 BHCs, the results presented in Appendix 3.3 Panel A show that banks' use of interest rate derivatives for hedging (*IRDs hedging*), traded on exchanged (*IRDs exchange*), and credit derivatives (*Net CDs*) increased their contribution to systemic risk without considering the effects of the DFA. The coefficient of *PostDFA* is significantly positive in columns (1) and (4) and negative in columns (3) and (6). The coefficients of the interaction terms (*IRDs hedging*PostDFA* in column (2), *IRDs exchange*PostDFA* in column (6) and *Net CDs*PostDFA* in columns (1) and (4)) suggest that the DFA effectively mitigated, even reversed, the impacts of these derivatives on banks' systemic risk. Interestingly, the coefficient of the interaction between *IRDs OTC* and *PostDFA* is found positive in column (6), indicating that interest rate derivatives traded OTC increased big banks' contribution to systemic risk after the signing of the DFA, although the coefficient is marginally significant.

As shown in Appendix 3.3 Panel B, the results of robustness tests on banks' risks also remain consistent with the main results presented previously in section 3.5. Big banks' use of interest rate derivatives for hedging (*IRDs hedging* in column (3)), interest rate derivatives traded on exchanged (*IRDs exchange* in column (6)) and credit derivatives (*Net CDs* in columns (2), (3), (5) and (6)) exposed them to higher risks without considering the effects of the DFA. Interest rate derivatives for trading (*IRDs trading* in columns (2) and (3)) and traded OTC (*IRDs OTC* in columns (5) and (6)) somehow lowered big bank's risks without considering the effects of the DFA. The coefficients of the interaction terms suggest that the signing of the DFA lessened the effects of *IRDs trading* (in column (2)), *IRDs hedging* (in column (3)) and *IRDs exchange* (in column (6)), and reversed the impact of *IRDs OTC* (in column (5)) and *Net CDs* (in columns (2), (3), (5) and (6)) on banks' risk. Regarding to the performance of big banks, the results in Appendix 3.3 Panel C indicate that the use of interest rate derivatives for trading (*IRDs trading and IRDs trading* PostDFA* in column (3)), traded OTC (*IRDs OTC and IRDs OTC*PostDFA* in column (6)) and credit derivatives (*Net CDs* in columns (1) and (4)) by big banks lowered their valuation.

3.6.2 Stress-tested banks

The second robustness test includes 18 banks that underwent stress tests during the study period, since these large banks were heavy users of derivatives prior to and during the GFC, and subject to heightened regulations from 2010 onwards (see Panels D, E, and F of Figure 3.1). This subsample includes the banks that are required to report the stress test results at year-end 2015.

The regression estimation for the stress-tested banks in Appendix 3.3 Panel D shows that credit derivatives use (*Net CDs*) in columns (1) and (4)) and interest rate derivatives held for hedging (*IRDs hedging*) in column (3)) by the stress-tested banks increased those banks' contribution to systemic risk without considering the effects of the DFA. However, the credit derivatives is found to decrease those banks' contribution to systemic risk after the signing of the DFA in columns (1) and (4)), when both the coefficients of *Net CDs* and *Net CDs*PostDFA* are considered.

As shown in Appendix 3.3 Panel E, consistent results are found for stress-tested banks that credit derivatives (*Net CDs*) in columns (2) and (5)) increased banks' risks without considering the effects of the DFA, while interest rate derivatives for trading

(*IRDs trading*) in column (2)) and traded OTC (*IRDs OTC*) in column (5)) decreased bank's risks without considering the effects of the DFA. The effect of interest rate derivatives for trading (*IRDs trading*PostDFA*) in column (2)) was effectively mitigated after the commencement of the DFA. The credit derivatives are found lowering stress-tested banks' valuation in the post-DFA period, as evidenced by the coefficients of *Net CDs* together with its interaction terms (*Net CDs*PostDFA*) in columns (2) and (5)).

However, the results in Appendix 3.3 Panel F about bank's performance are mixed across different measures, which suggests the impact of the DFA on mega banks' performance is likely to be more complicated relative to those on other banks and needs further investigation.

3.6.3 Alternative measurements

I applied another commonly used measure of systemic risk, namely capital shortfall (*SRISK*). *SRISK* is specified by Engle (2017) as a function of bank size (market value of equity), book value of liabilities, and long-run *marginal expected shortfall* (*MES*), namely the expected bank equity return conditional on the systemic event such as a stock market downturn. The formula used to compute SRISK is presented as below:

$$SRISK = \ (k * Dt - (1 - k) * e * (1 + MES)),$$

where k is the minimum capital ratio determined by regulation, *Dt* is the book value of a bank's total liabilities; e is the market value of a bank's equity. Following Laeven, Ratnovski, and Tong (2014) (2016), k is set at 8%. *MES* is the marginal expected shortfall as defined in Section 3.3.1. A high value of *SRISK* suggests high systemic risk. The results with *SRISK* as the measure of systemic risk is presented in Table 3.8. As shown in the table, the use of financial derivatives by banks increased their systemic risk without considering the effects of the DFA. Consistent with the results reported in Section 3.5, these effects are found mitigated, or even reversed, after the commencement of the DFA.

I also employ alternative measures for banks' characteristic variables in the regression models. For instance, both *leverage ratio* and *tier 1 ratio* measure banks' capital adequacy, while *non-performing loans* and *loan loss provision* are proxies for banks' loan loss risk. I employ *leverage ratio* and *non-performing loans,* which are found to have stronger impacts on systemic risk than derivatives holdings (Mayordomo, Rodriguez-Moreno, and Pena, 2014), as alternative measures for *tier 1 ratio* and *loan loss provision,* respectively in the model regression. Similarly, *return on equity* is applied as a substitute variable for *return on assets*, as the proxy for banks' performance. Additionally, I apply variables calculated with different confidence levels (*△CoVaR*, and *MES*) and time windows (*Z-score* and *Volatility*).

As shown in Appendix 3.3 Panel G, H, and I, I find mixed results on the effects of derivatives use by banks and the DFA as reported previously in Section 3.5.

Table 3.8 Results with alternative systemic risk measure (SRISK)

	(1)	(2)	(3)	(4)
IRDs trading	0.0015**	0.0011**		
IRDs hedging	0.0332*	0.0432**		
IRDs OTC			0.0018*	0.0017**
IRDs exchange			0.0191	0.0390**
Net CDs	0.1405	0.3871**	0.1394	0.3132***
Loan to depository institutions	-0.3490*	-0.2568*	-0.3977	-0.3577
Balance due from depository institutions	-1.4526	-1.5320*	-1.5151	-1.6789
Post DFA dummy		0.0016		0.0009
IRDs trading* PostDFA		0.0000		
IRDs hedging * PostDFA		-0.0271***		
IRDs OTC * PostDFA				0.0012*
IRDs exchange * PostDFA				-0.0243***
Net CDs * PostDFA		-0.8620***		-0.7322**
Size	-0.0035	-0.0032*	-0.0036	-0.0036
Tier 1 ratio	-0.0065	-0.0039	-0.0104	-0.0090
Loan Loss Provision	0.0006	0.0002	0.0006	0.0005
Book-to-market ratio	-0.0002	0.0000	-0.0003	-0.0002
Return on average assets	0.0105	0.0059	0.0078	0.0064
Short-term borrowing	0.0119	0.0011	0.0184	0.0191
Stock volatility	0.0694**	0.0421	0.0751**	0.0621**
Acquisition	0.0009	0.0010	0.0003	0.0002
Special capital users dummy	0.0011**	0.0006	0.0010**	0.0008**
Exposure to housing price change	-0.0051	-0.0022	-0.0030	-0.0021
HHI index	-0.0064*	-0.0054*	-0.0069*	-0.0061*
Intercept	0.0647*	0.0556*	0.0702	0.0646
Adj.R-squared	0.230	0.316	0.171	0.236
N	3563	3563	3563	3563

The dependent variable is the capital shortfall, *SRISK,* as an alternative systemic risk measure. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. *IRDs hedging* is defined as the notional amount of interest rate derivatives held not for trading purposes scaled by asset. . *IRDs OTC* is the notional amount of net long positions in interest rate derivatives traded OTC scaled by asset. *IRDs exchange* is the notional amount of net long positions in interest rate derivatives traded on exchange scaled by asset. *Net CDs* is defined as the credit derivatives bought minus credits derivatives sold, then scaled by asset. *Loan to depository institutions* is the ratio of Loan to depository institutions to total loans and leases. *Balance due from depository institutions* is the ratio of *Balance due from depository institutions* to total loans and leases. *PostDFA* is a dummy set to one after the Dodd-Frank Act is issued and zero otherwise. *Size* is calculated as the logarithm of total assets. *Exposure to housing price change* is a weighted average of the returns on the state-specific Fannie Mae real estate index where the weights are the fraction of bank deposits in the various states. *HHI index* is a weighted average of the *Herfindahl-Hirschman Index* where the weights are the fraction of bank deposits in the various states. *Special capital* is a dummy set to one if the bank uses any of the government bailout special capital programs. *Acquisition* is a dummy set to one if the bank acquires other banks in that quarter. All the estimated coefficients have been scaled by 10^6.For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

3.7 Conclusions

This study provides a comprehensive examination of the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) and how it impacted the use of derivatives products by U.S. banks. With a sample of 157 large U.S. bank holding companies, I examined the impacts of the use of derivatives and the DFA on banks' systemic risk through the central clearing channel (Title VII of the DFA) and the proprietary trading channel (the Volcker Rule of the DFA). In line with past studies prior to the DFA, I find that the excessive use of interest rate derivatives held for hedging, exchange-traded interest rate derivatives, and credit derivatives (traded OTC) substantially increased banks' contribution to systemic risk. More importantly, I show that in post-DFA periods, banks' contribution to systemic risk was substantially reduced, and the use of credit derivatives (traded OTC) and interest rate derivatives held for hedging have weakened impacts on bank's systemic risk in post-DFA periods. These findings provide supportive evidence on the effectiveness of the central clearing channel, showing that the implementation of the DFA mitigated the systemic risk associated with credit derivatives (traded OTC). However, by investigating banks' interest rate derivatives held for trading, I did not find any supportive evidence for the effectiveness of the proprietary trading channel under the DFA.

This study also investigates if the DFA induced higher risks in the banking sector at the individual bank level. However, the results are mixed regarding banks' credit risk and overall risk in post-DFA periods. In order to shed light on the risk-return profile of the U.S. banking sector, I also examined the impact of the DFA on banks' performance. Interestingly, I document evidence that the post-crisis period combined with the DFA regulatory environment resulted in a better performance for banks.

Given the debate on the repealing of the DFA proposed by Financial CHOICE Act, the results of this study provide tangible and important implications to banking regulators. Overall, the DFA achieved one of its objectives, namely, mitigating the impact of derivatives use on systemic risk. Post-DFA periods show less interconnectedness between banks caused by derivatives. Hence, the rolling back of the DFA could refuel the interconnectedness and systemic risk issues in the banking sector. On the other hand, the introduction of the DFA seems to be a great illustration of the well-known statement that the "risks do not disappear", as it is found that banks' individual risks increased at the same time when systemic risk went down.

Appendix 3.1

Hypotheses		***Findings***
H3-1a	***Banks' holdings of derivatives increase their contributions to systemic risk.***	Support
H3-1b	***The implementation of the DFA mitigates banks' contribution to systemic risk.***	Partly Support
H3-1c	***The implementation of the DFA reduces the impacts of derivatives holdings on banks' contribution to systemic risk.***	Partly Support
H3-2a	***Both interest rate derivatives used for trading and hedging increase banks' risk.***	Reject
H3-2b	***Credit derivatives increase banks' risk.***	Support
H3-2c	***Derivatives traded in OTC markets increase banks' risk, while derivatives traded on exchanges decrease banks' risk.***	Reject
H3-3	***The implementation of the DFA increases banks' risk.***	Support
H3-4	***Derivatives holdings improve banks' performance.***	Mixed
H3-5	***The implementation of the DFA decreases banks' performance.***	Support

Appendix 3. 2

Dependent Variables	Description	Relevant Literature
△CoVaR	The difference between the financial system's Value at Risk (VaR) conditional on bank *i*'s being in distress and the financial system's VaR in the median state of bank *i*. Bank *i*'s industry beta captures the sensitivity of its stock returns to the returns of the S&P Banks Selected Industry Index over a one-year period.	Trapp and Weiß (2016); Li and Marinč (2016); Mayordomo, Rodriguez-Moreno and Peña (2014);
MES	Marginal expected shortfall is defined as bank *i*'s mean return on days when the S&P Banks Selected Industry Index return reaches its lowest 5 percent level over a quarter period.	Li and Marinč (2016); Mayordomo, Rodriguez-Moreno and Peña (2014); Acharya, Pederseb, Philippon and Richardson (2017)
Banking industry beta	Sensitivity of stock daily return to the return of the S&P Banks Selected Industry Index based one-year time window	Nijskens and Wagner(2010)
Z-score	Sum of the mean return on assets and the mean ratios of equity to assets, divided by the standard deviation of the return on assets	Mohsni and Otchere (2014); Keppo and Korte (2016); Bolhat, Bolton and Lu (2015)
Distance to Default	Calculated as the market value of assets minus the default boundary (short term debt plus half long term debt), then scaled by the standard deviation of the market value of assets.	Eichler and Sobanski (2016); Jessen and Lando (2015) Hoque, Andriosopoulos and Douday (2015)
Value at Risk	The worst return that a bank expects to suffer at a confidence interval of 95 percent in a quarter.	Li and Marinč (2016); Williams (2016) Adrian and Brunnermeier (2014);
Stock volatility	Volatility of daily stock return in last 6 months	Trapp and Weiß (2016); Dang and Helwege (2017) Chiang, Chung and Louis (2017);
Tobin's Q	The ratio of market value to book value of total assets	Chen, Li, Luo and Zhang (2017); Bhandari and Javakhadze (2017) Zeidan and Shapir (2017)
Cost-to-income ratio	Operating expense as a percentage of operating income	Borio, Gambacorta, and Hofmann (2017); Almazari (2014); Pelletier (2018) Bitar, Pukthuanthong, and Walker (2017);
Return on Asset	Net income as a percentage of assets	Berger, Black, Bouwman and Dlugosz (2014); Beck, Chen, Lin and Song (2016); Dang and Helwege (2017)

Independent Variables	Description	Relevant Literature
IRDs trading	The notional amount or par value of all off-balance-sheet interest rate derivative contracts held for trading purposes reported in Y9 call report, and then scaled by the bank's total asset.	Li and Marinč (2016); Li and Marinč (2014); Mayordomo, Rodriguez-Moreno and Peña (2014)
IRDs hedging	The notional value or par value of interest rate off-balance-sheet derivative contracts held for purposes other than trading reported in Y9 call report, and then scaled by the bank's total asset	Li and Marinč (2016); Li and Marinč (2014); Mayordomo, Rodriguez-Moreno and Peña (2014)
Net CDs (traded OTC)	The net notional amount is calculated as the notional amount of all credit derivatives for which the bank has obtained a guarantee against credit losses from other parties, minus the notional amount of all credit derivatives for which the bank has extended credit protection to others, then scaled by the bank's total asset. According to SNL database, credit derivatives reported are all traded in OTC market.	Li and Marinč (2014); Hirtle (2009); Minton, Stulz and Williamson (2009)
IRDs OTC	Sum of the notional amount of interest rate forwards, interest rate swaps and the net long positions in OTC interest rate options scaled by the bank's total asset	-
IRDs exchanges	Sum of the notional amount of interest rate futures and net long positions in exchange-traded interest rate options scaled by the bank's total asset.	-
Loan to depository institutions	Loans to all depository institutions as a percentage of gross loans and leases	Mayordomo, Rodriguez-Moreno and Peña (2014)
Balance due from depository institutions	Balance due from depository institutions as a percentage of gross loans and leases	Mayordomo, Rodriguez-Moreno and Peña (2014)
Loan loss provision	Loan loss provisions as a percentage of net interest income	Dang and Helwege (2017); Li and Marinč (2014); Li and Marinč (2016)
Tier 1 ratio	Tier 1 capital as a percentage of total risk-weighted assets	Berger, Black,Bouwman and Dlugosz (2014); Li and Marinč (2016); Dang and Helwege (2017)

Independent Variables

PostDFA	Dummy equals to one after the DFA was singed into the federal law on July 21, 2010	Cumming, Dai and Johan (2017); Keppo and Korte (2016); Sorokina and Thornton (2016)
Size	Logarithm of total asset	Mayordomo, Rodriguez-Moreno and Peña (2014); Berger and Roman (2015); Li and Marinč (2017)
Special capital users dummy	Dummy equals to one if a bank disclosed to use the discount window borrowing or any of the four special capital programs namely troubled asset relief program (TARP), term securities lending facility, term auction facility and primary dealer credit facility.	Dang and Helwege (2017); Berger and Roman (2015); Berger, Black, Bouwman and Dlugosz (2014)
Exposure to housing price change	The average weighted housing return derived by using the proportion of deposits a bank has in each state.	Dang and Helwege (2017)
HHI index	The average weighted Herfindahl-Hirschman Index derived by using the proportion of deposits a bank has in each state,	Berger and Roman (2015)
Book-to-market ratio	Book value of total equity as a percentage of market capitalization	Dang and Helwege (2017); Bhandari and Javakhadze (2017); Weiß, Bostandzic and Neumann (2014)
Short-term borrowing	Borrowings with a maturity of one year or less as a percentage of asset	Mayordomo, Rodriguez-Moreno and Peña (2014);
Acquisition	Dummy equals to one if a bank acquired another bank in that quarter	Dang and Helwege (2017);
Liquid	The sum of cash and cash equivalents as a percentage of asset	Li and Marinč (2017); Li and Marinč (2014); Dang and Helwege (2017);
Beta	Sensitivity of stock daily return to the return of the S&P 500 Index based on one-year time window	Li and Marinč (2017); Dang and Helwege (2017); Trapp and Weiß (2016);

Appendix 3.3

Robustness test results Panel A

	(1) △CoVaR	(2) MES	(3) Bank beta	(4) △CoVaR	(5) MES	(6) Bank beta
IRDs trading	-0.0001	0.0000	0.0046			
IRDs hedging	-0.0124**	-0.0117*	0.2054***			
IRDs OTC				-0.0002	0.0002	0.0074
IRDs exchange				-0.0178*	-0.0175**	0.2493***
Net CDs	-0.1324***	-0.1088	0.8797	-0.1128***	-0.0941	0.5323
Loan to depository institutions	0.0526	0.1580	2.0091**	0.0891	0.2094*	1.4573
Balance due from depository institutions	1.4685**	-0.2547	4.2416	1.5795**	-0.1147	2.5296
Post DFA dummy	0.0137***	-0.0016	-0.2377***	0.0144***	0.0005	-0.2446***
IRDs trading* PostDFA	-0.0000	-0.0003	0.0018			
IRDs hedging * PostDFA	0.0062	0.0196***	-0.0633			
IRDs OTC * PostDFA				-0.0005	-0.0003	0.0112*
IRDs exchange * PostDFA				0.0086	0.0048	-0.1674**
Net CDs * PostDFA	0.3473***	0.1731	-1.2080	0.3086***	0.1796	-0.2572
Size	-0.0020	-0.0081**	0.0260	-0.0017	-0.0077**	0.0198
Tier 1 ratio	-0.0362	-0.0419	0.1525	-0.0328	-0.0354	0.0959
Loan Loss Provision	-0.0025	-0.0064**	0.0175	-0.0025	-0.0067**	0.0191
Book-to-market ratio	-0.0009	-0.0024	-0.0007	-0.0008	-0.0021	-0.0022
Return on average assets	-0.0240	-0.1016	0.5723	-0.0242	-0.1027	0.5816
Short-term borrowing	-0.0592**	-0.0033	-0.2758	-0.0623**	-0.0071	-0.2224
Stock volatility	-0.0440	-0.4235***	9.4489***	-0.0541	-0.4542***	9.5501***
Acquisition	0.0016	-0.0002	-0.0353*	0.0022	0.0005	-0.0444**
Special capital users dummy	-0.0014	-0.0015	0.0020	-0.0015	-0.0018	0.0042
Exposure to housing price change	-0.0215	0.0322	0.0996	-0.0238	0.0332	0.1372
HHI index	-0.0034	0.0032	-0.0241	-0.0034	0.0029	-0.0252
Intercept	0.0130	0.0609	0.7195	0.0096	0.0570	0.8005
Adj.R-squared	0.604	0.745	0.454	0.597	0.757	0.463
N	1210	1210	1210	1210	1210	1210

This table represents the results of the robustness test on systemic risk within a subsample of big banks (see Section 3.6.1). The dependent variables in the regressions are change in conditional Value at Risk at 95 percent (*△CoVaR*), marginal expected shortfall at 95 percent (*MES*) and banking industry beta (*Bank beta*) calculated using one year of daily stock price. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel B

	(1) Z-score	(2) Distance to Default	(3) Volatility	(4) Z-score	(5) Distance to Default	(6) Volatility
IRDs trading	0.0260	0.0332**	-0.0004***			
IRDs hedging	2.1363	-0.0463	0.0059*			
IRDs OTC				0.0866	0.0457**	-0.0006***
IRDs exchange				-0.5683	-0.4308	0.0097**
Net CDs	-21.4410	-23.6737***	0.1796*	-28.3312	-23.8568***	0.1736**
Post DFA dummy	-5.7504***	-3.3745***	-0.0007	-5.9294***	-3.3696***	-0.0016
IRDs trading* PostDFA	0.0061	-0.0310***	-0.0001			
IRDs hedging * PostDFA	-1.0792	0.1530	-0.0121***			
IRDs OTC * PostDFA				-0.0491	-0.0523**	0.0001
IRDs exchange * PostDFA				1.5162	0.4798	-0.0077*
Net CDs * PostDFA	-15.5108	35.7201***	-0.2616**	-11.9097	35.3344***	-0.2636***
Size	1.1128	0.4849	0.0020	1.2923	0.4754*	0.0025
Tier 1 ratio	2.4201	0.5959	-0.0445*	1.7216	0.4489	-0.0445*
Loan Loss Provision	-0.0540	-0.1036	0.0032*	-0.0624	-0.1070	0.0034*
Book-to-market ratio	0.0126	0.0676	0.0084***	-0.0013	0.0688	0.0084***
Return on average assets			-0.0261			-0.0256
Short-term borrowing	11.9333**	-2.9851	0.0143	12.1386**	-3.0048	0.0156
Stock volatility	0.3398	-16.7025***		2.3173	-16.7817***	
Acquisition	-0.5556	-0.2284	-0.0011	-0.5855	-0.2223	-0.0013**
Special capital users dummy	-0.0270	-0.1346	0.0017**	-0.0182	-0.1351	0.0018**
Exposure to housing price change	-24.3314**	-6.7183*	0.0036	-23.5133**	-6.7648*	0.0052
HHI index	-1.7732	0.2659	-0.0005	-1.6222	0.2750	-0.0003
Intercept	8.6308	0.7982	-0.0082	6.0464	0.8604	-0.0151
Adj.R-squared	0.443	0.589	0.883	0.442	0.579	0. 886
N	1173	1173	1173	1173	1173	1173

This table represents the results of the robustness test on banks' credit risk and overall risk within a subsample of big banks (see Section 3.6.1). The dependent variables in the regressions are Z-score, distance to default, and six-month stock price volatility. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel C

	(1) Tobin's Q	(2) ROA	(3) Cost to Income	(4) Tobin's Q	(5) ROA	(6) Cost to Income
IRDs trading	0.0019	-0.0001	0.0073*			
IRDs hedging	0.0826	0.0073	-0.1127			
IRDs OTC				0.0012	0.0002	0.0076*
IRDs exchange				0.2460	-0.0075	0.0743
Net CDs	0.1455	0.0962	-1.1119	-0.0508	0.0802	-0.9642
Post DFA dummy	0.0694	-0.0014	0.0453	0.0715	-0.0017	0.0594*
IRDs trading* PostDFA	-0.0040**	-0.0002	0.0060***			
IRDs hedging * PostDFA	-0.0308	0.0002	0.1212*			
IRDs OTC * PostDFA				0.0019	0.0002	0.0075*
IRDs exchange * PostDFA				-0.1365*	-0.0041	-0.0345
Net CDs * PostDFA	-1.1009	-0.1600	2.0663	-0.5143	-0.1023	2.0735
Size	-0.1405*	-0.0041	-0.0503	-0.1383*	-0.0034	-0.0620
Tier 1 ratio	-1.5397*	0.1283**	-0.8502	-1.5441*	0.1256**	-0.8075
Loan Loss Provision	-0.0734***	-0.0069	-0.0391	-0.0743***	-0.0068	-0.0417
Book-to-market ratio		-0.0086***	0.1052**		-0.0088***	0.1072**
Return on average assets	0.1970		-2.3607***	0.2007		-2.4041***
Short-term borrowing	-0.0410	0.0154	-0.1971	-0.0178	0.0161	-0.2001
Stock volatility	-0.6138	-0.2535**	1.6359	-0.5796	-0.2579**	1.4947
Acquisition	0.0123	-0.0012	-0.0086	0.0075	-0.0013	-0.0074
Special capital users dummy	0.0119	0.0004	-0.0236	0.0125	0.0003	-0.0243
Exposure to housing price change	1.6221***	0.0655	-0.4742	1.6370***	0.0678	-0.5030
HHI index	-0.0435	0.0012	-0.0081	-0.0397	0.0013	-0.0136
Intercept	3.0097***	0.0423	1.1504**	2.9556***	0.0364	1.2869***
Adj.R-squared	0.512	0.176	0.108	0.518	0.168	0.107
N	1173	1126	1113	1173	1126	1113

This table represents the results of the robustness test on banks' performance within a subsample of big banks (see Section 3.6.1). The dependent variables in the regressions are *Tobin's Q*, return on assets (*ROA*), and *cost to income*. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel D

	(1) △CoVaR	(2) MES	(3) Bank beta	(4) △CoVaR	(5) MES	(6) Bank beta
IRDs trading	-0.0004	-0.0002	0.0015			
IRDs hedging	-0.0091	-0.0006	0.1035*			
IRDs OTC				-0.0006	-0.0000	0.0020
IRDs exchange				-0.0065	-0.0071	0.0593
Net CDs	-0.0913*	0.0439	0.4512	-0.0744*	0.0283	0.5848
Loan to depository institutions	0.0824	0.1842***	2.9373***	0.1137	0.1893***	2.7017***
Balance due from depository institutions	1.6350	1.4421*	1.1414	1.8107	1.4043*	0.3599
Post DFA dummy	0.0059	-0.0003	0.0904	0.0052	0.0004	0.1104
IRDs trading* PostDFA	-0.0002	-0.0004**	0.0015			
IRDs hedging * PostDFA	0.0078	0.0003	0.0642			
IRDs OTC * PostDFA				-0.0004	-0.0002	0.0057
IRDs exchange * PostDFA				0.0040	-0.0030	-0.0411
Net CDs * PostDFA	0.2300**	-0.1058	0.0611	0.1962*	-0.0667	0.4348
Size	-0.0032	-0.0137***	-0.1425**	-0.0004	-0.0139***	-0.1616**
Tier 1 ratio	0.1613	0.1920*	-2.1979*	0.1813	0.1972*	-2.1786*
Loan Loss Provision	-0.0092	-0.0127***	0.0438	-0.0095	-0.0123***	0.0445
Book-to-market ratio	0.0019	-0.0068**	0.0460**	0.0024	-0.0071**	0.0438*
Return on average assets	-0.0630	-0.2862**	0.9000**	-0.0632	-0.2861**	0.8400**
Short-term borrowing	-0.0373	0.0318	-1.2739***	-0.0371	0.0326	-1.2818***
Stock volatility	-0.0912	-0.2753	7.1140***	-0.1117	-0.2743	7.1517***
Acquisition	0.0002	-0.0016	-0.0462	0.0012	-0.0014	-0.0557
Special capital users dummy	0.0008	-0.0030	0.0131	0.0009	-0.0031	0.0117
Exposure to housing price change	0.1589	0.0535	0.4562	0.1889	0.0440	0.2873
HHI index	0.0086	0.0096	-0.0587	0.0089	0.0088	-0.0655
Intercept	-0.0635	0.0843	3.0720***	-0.1025	0.0929	3.3645***
Adj.R-squared	0.667	0.681	0.436	0.642	0. 678	0.417
N	354	354	354	354	354	354

This table represents the results of the robustness test on systemic risk within a subsample of stress-tested banks (see Section 3.6.2). The dependent variables in the regressions are change in conditional Value at Risk at 95 percent (*△CoVaR*), marginal expected shortfall at 95 percent (*MES*) and banking industry beta (*Bank beta*) calculated using one year of daily stock price. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel E

	(1) Z-score	(2) Distance to Default	(3) Volatility	(4) Z-score	(5) Distance to Default	(6) Volatility
IRDs trading	-0.0463	0.0403*	-0.0002			
IRDs hedging	3.7055	0.0342	0.0016			
IRDs OTC				0.0074	0.0552**	-0.0003
IRDs exchange				-0.2684	0.1122	0.0048
Net CDs	-15.4775	-26.6015***	0.0543	-21.7875	-27.3061***	0.0531
Post DFA dummy	-8.7746***	-3.1323***	-0.0003	-9.3154***	-3.1238***	-0.0007
IRDs trading* PostDFA	-0.0362	-0.0364***	-0.0000			
IRDs hedging * PostDFA	-1.5360	-0.0179	-0.0039			
IRDs OTC * PostDFA				0.0263	-0.0287	0.0000
IRDs exchange * PostDFA				-0.4350	-0.2100	-0.0018
Net CDs * PostDFA	-23.2705	33.8473***	-0.0855	-11.8846	35.2222***	-0.0913
Size	4.5881	0.7742	0.0010	5.2487*	0.7476	0.0010
Tier 1 ratio	9.3786	3.1528	-0.0891*	9.7120	3.1559	-0.0938*
Loan Loss Provision	-1.1829	-0.3662	0.0078**	-1.2137	-0.3622	0.0077**
Book-to-market ratio	0.3703	0.2207**	0.0099***	0.2874	0.2215*	0.0099***
Return on average assets			0.0388			0.0410
Short-term borrowing	3.6673	-0.9701	0.0162	2.4950	-0.8087	0.0144
Stock volatility	30.4012	-7.1975		33.7784	-7.3461	
Acquisition	0.6941	-0.0064	0.0002	0.5745	-0.0128	0.0001
Special capital users dummy	0.5033	0.0778	0.0021	0.4685	0.0760	0.0022
Exposure to housing price change	-18.4696	2.4122	0.0376	-18.1029	2.1973	0.0398
HHI index	-2.1963*	0.5322	-0.0006	-2.2696*	0.5165	-0.0003
Intercept	-33.4750	-5.4068	0.0009	-40.3959	-5.0320	-0.0017
Adj.R-squared	0.263	0.733	0.893	0.373	0.760	0.827
N	382	382	382	382	382	382

This table represents the results of the robustness test on banks' credit risk and overall risk within a subsample of stress-tested banks (see Section 3.6.2). The dependent variables in the regressions are Z-score, distance to default, and six-month stock price volatility. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel F

	(1) Tobin's Q	(2) ROA	(3) Cost to Income	(4) Tobin's Q	(5) ROA	(6) Cost to Income
IRDs trading	-0.0001	-0.0007*	0.0136**			
IRDs hedging	0.0040	0.0028	-0.0146			
IRDs OTC				-0.0003	-0.0007	0.0161**
IRDs exchange				0.1932	-0.0064	0.1247
Net CDs	0.8284	0.2244*	-2.0341	0.5834	0.2265*	-2.0426
Post DFA dummy	-0.1187*	0.0106*	0.0178	-0.1066*	0.0097	0.0315
IRDs trading* PostDFA	-0.0014	-0.0004**	0.0072***			
IRDs hedging * PostDFA	0.0128	-0.0042	0.0832			
IRDs OTC * PostDFA				0.0030	0.0001	0.0116*
IRDs exchange * PostDFA				-0.1113	-0.0088	-0.0974
Net CDs * PostDFA	-2.1983	-0.3546**	3.3511**	-1.6072	-0.3190**	3.7231**
Size	-0.0693	0.0026	0.0881	-0.0541	0.0043	0.0725
Tier 1 ratio	0.4014	0.1339*	-0.0766	0.4102	0.1297	0.0365
Loan Loss Provision	-0.0844**	-0.0186	-0.1397	-0.0944**	-0.0182	-0.1480
Book-to-market ratio		-0.0028	-0.0525		-0.0030	-0.0487
Return on average assets	0.8311*		-7.5142	0.7829*		-7.7978
Short-term borrowing	-0.2498	-0.0923	0.3034	-0.2447	-0.0963	0.3408
Stock volatility	0.3516	-0.7323**	5.8412	0.1180	-0.7318**	5.6726
Acquisition	-0.0030	-0.0079	0.0654*	-0.0041	-0.0079	0.0614
Special capital users dummy	-0.0267*	-0.0030	0.0695*	-0.0233	-0.0033	0.0704*
Exposure to housing price change	-1.0288	0.1383	-2.6511	-0.8254	0.1266	-2.5243
HHI index	-0.1377***	-0.0058	-0.0164	-0.1279**	-0.0073	-0.0168
Intercept	2.9551**	0.0303	-0.3594	2.6711***	0.0217	-0.2017
Adj.R-squared	0.559	0.384	0.149	0.576	0.387	0.149
N	315	290	280	315	290	280

This table represents the results of the robustness test on banks' performance within a subsample of stress-tested banks (see Section 3.6.2). The dependent variables in the regressions are *Tobin's Q*, return on assets (*ROA*), and *cost to income*. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel G

	(1) △CoVaR	(2) MES	(3) Bank beta	(4) △CoVaR	(5) MES	(6) Bank beta
IRDs trading	-0.0003**	-0.0002	0.0078			
IRDs hedging	-0.0155***	-0.0183**	0.1871***			
IRDs OTC				-0.0005*	0.0000	0.0126
IRDs exchange				-0.0192*	-0.0159	0.2619**
Net CDs	-0.2196***	-0.3485***	2.1107*	-0.1844***	-0.3350***	1.4349*
Loan to depository institutions	0.0674	0.2313	0.4247	0.0984	0.2921	0.2164
Balance due from depository institutions	0.7808***	-1.0442	3.3336	0.7969**	-1.0148	3.2723
Post DFA dummy	0.0117***	-0.0027	-0.3996***	0.0119***	-0.0017	-0.3969***
IRDs trading* PostDFA	-0.0001	-0.0002	0.0030			
IRDs hedging * PostDFA	0.0118***	0.0284***	-0.0361			
IRDs OTC * PostDFA				-0.0005	-0.0000	0.0129**
IRDs exchange * PostDFA				0.0091	0.0029	-0.1741**
Net CDs * PostDFA	0.4878***	0.4292***	-3.3087	0.4414***	0.4527***	-2.0571
Size	-0.0011	-0.0077***	0.1740***	-0.0010	-0.0077**	0.1714***
Leverage	-0.0140*	-0.0026	0.0528	-0.0179**	-0.0087	0.0899
Non-performing loans	-0.0618***	0.0051	-1.0476	-0.0541**	0.0166	-1.1214*
Book-to-market ratio	-0.0001	0.0018*	-0.0321***	-0.0001	0.0018*	-0.0325***
Return on average equity	-0.0005	0.0044*	0.0172	-0.0004	0.0045*	0.0151
Short-term borrowing	-0.0715***	-0.0657*	-0.1560	-0.0761***	-0.0729**	-0.1108
Stock volatility	-0.1027***	-0.3692***	8.9064***	-0.1142***	-0.3913***	8.9808***
Acquisition	0.0007	-0.0000	-0.0483***	0.0010	0.0004	-0.0515***
Special capital users dummy	-0.0008	-0.0006	-0.0010	-0.0009	-0.0007	-0.0008
Exposure to housing price change	0.0140	0.0829**	-0.1286	0.0126	0.0820**	-0.1098
HHI index	0.0008	0.0038	0.0203	0.0010	0.0037	0.0173
Intercept	-0.0181	0.0370	-0.7003*	-0.0196	0.0374	-0.6615*
Adj.R-squared	0.632	0.610	0.405	0.630	0.608	0.405
N	3485	3485	3485	3485	3485	3485

This table represents the results of the robustness test on systemic risk with alternative measures (see Section 3.6.3). The dependent variables in the regressions are change in conditional Value at Risk at 95 percent (△*CoVaR*), marginal expected shortfall at 95 percent (*MES*) and banking industry beta (*Bank beta*) calculated using one year of daily stock price. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel H

	(1) Z-score	(2) Distance to Default	(3) Volatility	(4) Z-score	(5) Distance to Default	(6) Volatility
IRDs trading	-0.0327	-0.0002	-0.0003***			
IRDs hedging	-0.9056	-0.4515	0.0105***			
IRDs OTC				-0.0174	0.0262	-0.0004***
IRDs exchange				-0.1307	-0.3067	0.0089
Net CDs	-20.9091	-20.4498***	0.2053**	-22.9773	-23.4245***	0.1864**
Post DFA dummy	-6.2682***	-2.8807***	0.0136***	-6.3107***	-2.8641***	0.0133***
IRDs trading* PostDFA	0.0293	-0.0315***	-0.0001			
IRDs hedging * PostDFA	-0.3495	0.5177	-0.0156***			
IRDs OTC * PostDFA				-0.0134	0.0039	-0.0000
IRDs exchange * PostDFA				0.5367	-0.5483	-0.0045
Net CDs * PostDFA	-6.6205	29.3624***	-0.2604***	-8.8848	36.0161***	-0.2563**
Size	0.8186	0.4091***	0.0010	0.8309	0.4033***	0.0010
Leverage	3.8144	0.7167	-0.0020	3.5684	0.5639	0.0017
Non-performing loans	-3.5652	-8.5372***	0.1056***	-3.4773	-8.3053***	0.1015**
Book-to-market ratio	0.0479	0.1270***	0.0062***	0.0533	0.1272***	0.0062***
Return on average equity			-0.0061***			-0.0062***
Short-term borrowing	8.7837*	-4.9857**	0.0254**	8.7668*	-5.0986**	0.0299**
Stock volatility	-7.3517	-18.8178***		-7.4991	-19.2707***	
Acquisition	-0.1759	-0.0428	0.0001	-0.1677	-0.0301	-0.0002
Special capital users dummy	-0.0061	-0.0214	0.0008*	-0.0039	-0.0256	0.0009*
Exposure to housing price change	-6.9451	0.0112	-0.0288*	-6.9771	-0.0077	-0.0293*
HHI index	0.0946	-0.0486	-0.0006	0.1182	-0.0465	-0.0007
Intercept	0.1654	2.7854	0.0049	-0.1055	2.8208	0.0060
Adj.R-squared	0.401	0.588	0.819	0.401	0.588	0.817
N	3826	3826	3826	3826	3826	3826

This table represents the results of the robustness test on banks' credit risk and overall risk within alternative measures (see Section 3.6.3). The dependent variables in the regressions are Z-score, distance to default, and six-month stock price volatility. *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

Robustness test results Panel I

	(1) Tobin's Q	(2) ROA	(3) Cost to Income	(4) Tobin's Q	(5) ROA	(6) Cost to Income
IRDs trading	0.0030	0.0001	-0.0011			
IRDs hedging	0.1480**	-0.0114	0.0624			
IRDs OTC				0.0054	0.0003	0.0027
IRDs exchange				0.1899**	-0.0028	0.0481
Net CDs	-0.0570	0.0050	0.6707	-0.3588	-0.0208	0.0400
Post DFA dummy	0.0416	0.0086***	-0.0236	0.0488	0.0084***	-0.0206
IRDs trading* PostDFA	-0.0056*	-0.0000	0.0057**			
IRDs hedging * PostDFA	0.0466	0.0037	0.0008			
IRDs OTC * PostDFA				0.0029	-0.0000	0.0148***
IRDs exchange * PostDFA				-0.1349***	-0.0008	-0.1498**
Net CDs * PostDFA	-0.8438	0.0227	0.3546	-0.0717	0.0577	1.7035
Size	-0.0145	-0.0132***	-0.0267	-0.0171	-0.0132***	-0.0290
Leverage	0.0186	0.0021	0.0048	0.0467	-0.0015	0.0209
Non-performing loans	-2.1935***	-0.1688***	1.5341***	-2.2398***	-0.1656***	1.5207***
Book-to-market ratio		-0.0027***	0.0125		-0.0027***	0.0121
Return on average equity	0.0138		-0.0474	0.0122		-0.0480
Short-term borrowing	0.0881	0.0143	-0.3320	0.1103	0.0122	-0.3121
Stock volatility	-0.7623*	-0.0571	1.5981**	-0.7513*	-0.0632	1.6073**
Acquisition	0.0124	-0.0003	0.0021	0.0104	-0.0001	0.0016
Special capital users dummy	0.0041	-0.0003	-0.0098	0.0040	-0.0003	-0.0100
Exposure to housing price change	1.1303***	0.1287***	-1.1376**	1.1458***	0.1284***	-1.1398**
HHI index	0.0309	0.0022	-0.0045	0.0273	0.0024	-0.0066
Intercept	1.1315*	0.1123***	0.8494***	1.1754*	0.1102***	0.8806***
Adj.R-squared	0.434	0.177	0.053	0.433	0.175	0.053
N	3826	3826	3826	3826	3826	3826

This table represents the results of the robustness test on banks' performance within alternative measures (see Section 3.6.3). The dependent variables in the regressions are *Tobin's Q*, return on assets (*ROA*), and *cost to income.* *IRDs trading* is the notional amount of interest rate derivatives held for trading purposes scaled by asset. The definitions of other independent variables are the same as in Section 3.4. For brevity reasons, time fixed effects and firm fixed effects are not reported. Standard errors are heteroskedasticity-consistent.

PART III

CONCLUSION

My thesis examines three different research questions in the area of derivatives. The obtained answers allow academics, industry practitioners, and regulators to better understand the complexity of derivatives markets.

The first essay examines the impacts of fund flows to VIX ETPs on the level of the underlying VIX index. I find that the fund flows into different VIX ETP groups significantly impact the VIX index. However, no evidence shows that there are additional impacts of the fund flows to VIX ETPs on the underlying VIX index during high-volatility times. These findings are an important voice in the debate that money flows into VIX ETPs could create distortions and broadly affect the underlying VIX, especially during volatile periods (Alexander and Korovilas, 2012; Asensio, 2013). The results also provide valuable implications to the market regulator, the Security and Exchange Commission, which raised concerns between ETPs and underlying assets. An interesting area for future research would be to test the difference in fund flows from institutional investors and individual investors to VIX ETPs, particularly when the market is volatile

In the second essay, I analyze the relationship between the VIX and economic policy uncertainty by empirically testing the implication of the theoretical models of Pastor and Veronesi (2013) and Dumas, Kurshev, and Uppal (2009). I find that the relationship is affected by factors such as the quality of political signals, investors' opinion divergence and representativeness bias. These results show that the relationship between expected market volatility and its determinants is subject to changes over time and is not as simple as past studies assumed. Future research should focus on the development of a theoretical model that could explain the complex relationship between market volatility, policy uncertainty and those factors discussed.

My third essay examines the effects of the Dodd-Frank Act on the use of derivatives products by U.S. bank holding companies. The findings show that the implementation of the Dodd-Frank Act mitigated the systemic risk associated with derivatives; however, it increased banks' individual risks at the same time. These results indicate that regulations in the post-crisis period changed banks' attitudes towards derivatives. An interesting extension of this work would be to examine the channels via which banks' systemic risks affect and interact with their overall risks and credit risks.

Overall, the findings of my thesis suggest that financial derivatives are a double-edged sword. On the one hand, derivatives used for risk management purposes benefit investors by hedging risks associated with their investment portfolios. On the other hand, derivatives could pose higher risks for investors and even jeopardize the stability of the whole financial market. Derivatives also require deeper understanding on how they impact the environments in which they are traded. My work provides evidence to academics, practitioners and regulators that derivatives trading could affect the underlying, but such an effect is not stronger during market downturns; that changes in margin requirements can be an effective tool for exchanges to influence the trading patterns of derivatives; that derivatives regulations might face a trade-off between mitigating one type of risk and increasing other risks. The latter is a good reminder that derivatives are used for risk transferring rather than risk elimination.

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