EMPIRICAL STUDIES ON SYSTEMIC RISK:

IMPLICATIONS AND DETERMINANTS

AFSHIN SABRI

Doctor of Philosophy

ASTON UNIVERSITY

September 2020

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THESIS SUMMARY

This thesis is composed of three separate empirical studies focusing on financial institutions and systemic risk. The aim of the studies is to investigate the possible implications and determinants of financial institutions' systemic risk.

Study I analyses the role of systemic risk in how US financial sector stocks react to interest rate changes, under different macroeconomic conditions. Using an event study methodology, we document that systemic risk has a significant impact on the reaction of financial stocks to monetary policy announcements. Overall, our findings suggest that financial institutions with high systemic risk tend to benefit from the "Too-Big-To-Fail" advantage whenever interest rates are unexpectedly high, or the yield curve is relatively flat (i.e. the macroeconomic risk is high).

Study II investigates the bidirectional relationship between systemic risk and bank liquidity creation in a Bayesian panel vector autoregressive framework. Analysing a sample of US banks, we find that liquidity creation has a significant impact on bank systemic risk. Although different forms of liquidity creation affect systemic risk in opposite directions, the overall effect tends to be positive. Furthermore, we find that shocks to systemic risk also lead to significant rises in liquidity creation, suggesting strong feedback effects between liquidity creation and systemic risk.

Study III aims to examine the potential consequences of the COVID-19 crisis for idiosyncratic and systemic risk in the US financial system. We find that both idiosyncratic and systemic risk of the large financial institutions in the US have substantially increased in the wake of the COVID-19 pandemic. Our results show that the rise in financial system risk in this period has been driven by the number of COVID-19 infections as well as the government's restrictive policies.

A more detailed abstract of each study can be found on the first page of each study.

Keywords: systemic risk, financial stocks, monetary policy, liquidity creation, COVID-19

AKCNOWLEDGEMENTS

My PhD experience has taught me a lot and has faced me with countless challenges. I would like to thank anyone who has helped me successfully go through this journey, especially my supportive supervisors, Prof. Enrico Onali and Dr. Dudley Gilder, who continued to supervise my research even though they left Aston University. I would also like to say thank you to Dr. Matthew Olczak and everyone in the RDP team and the EFE group for all their help and guidance.

I should also say thank you to all my friends in Aston, SinMun, Andrii, Parixit, Kristina, Karishma, Uzy, Diya, Monty and everybody else with whom I shared my PhD journey. You guys made it much more fun!

Finally, I cannot forget to thank my family, who have always been my pillar of strength, despite being thousands of miles apart. Thank you all!

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STUDY I:

Systemic Risk, Macroeconomic Environment and Stock Price Reaction to Monetary Policy News

Abstract

We employ an event study approach to estimate the price reaction of US financial stocks to 147 Federal funds target rate announcements. We show that systemic risk increases abnormal returns for announcements related to a positive unexpected change in the target rate ("Positive Surprise") or whenever the announcements are associated with a flattening yield curve. Conversely, systemic risk tends to reduce abnormal returns for "Negative Surprises" and "Zero Surprises" (when the announced rate is the same as the expected one). These results suggest that a higher than expected target rate can be advantageous to institutions with high levels of systemic risk. High short-term interest rates and a flat yield curve can increase the risk of a crisis, and thus this finding is consistent with a "Too-Big-To-Fail (TBTF) hypothesis": whenever the likelihood of a systemic crisis increases, investors buy stocks of financial firms that are more likely to be rescued.

Keywords: systemic risk; monetary policy; interest rate; too big to fail; event study

1. Introduction

Central banks use monetary policy interventions to stimulate the economy during recessions and slowdown periods, or to control the inflation in periods of high economic growth. The mechanism through which monetary policy affects the real economy (the monetary policy transmission channel) has been subject to debate for a long period of time (Borio and Zhu 2012). Changes in interest rates (i.e., conventional monetary policy measures) have a widespread impact on the banking and financial sector and in particular they might affect the lending supply of banks, which in turn influences the real economy. Therefore, the financial system is a key component of the monetary policy transmission channel.[1]

For non-financial firms, announcements of an interest rate reduction (increase) are usually regarded as positive (negative) news and are often accompanied by a concomitant increase (decrease) in stock prices (Bernanke and Kuttner 2005). In the case of financial institutions, however, this relation is more complex. While some bank-specific variables such as deposit funding and maturity mismatches might have an impact on how bank stock prices react to conventional monetary policy interventions (English, Van den Heuvel, and Zakrajšek 2018; Heider, Saidi, and Schepens 2019; Ricci 2015), the potential effect of systemic risk on the price reaction to such measures has never been investigated. This is the focus on this paper.

Studying the price impact of conventional monetary policy measures on systemically important financial institutions (SIFIs) is important for financial stability and risk management. The monetary policy actions that destabilise financial institutions with high systemic risk can have a detrimental effect on the rest of the system. After the 2007-2009 financial crisis, macroprudential regulatory measures, such as Basel III, were introduced to mitigate the potential negative externalities of systemic risk on the economy. Among central bank decision-makers, the debate over the financial stability impact of

[1] There is evidence that bank risk taking is influenced by monetary policy decisions (Bekaert, Hoerova, and Lo Duca 2013; Dell'Ariccia, Laeven, and Suarez 2017; Paligorova and Santos 2017).

monetary policy has been ongoing for a long time. For example, Lael Brainard, a member of the Federal Reserve Board of Governors, said in a speech in September 2020 that[2]:

"The resulting expectation of lower-for-longer interest rates, along with sustained high rates of resource utilization, is conducive to increasing risk appetite, reach-for-yield behaviour, and incentives for leverage—which can boost financial imbalances as an expansion extends."

On the other hand, other monetary policy officials argue that there is not a very strong connection between lax monetary policy and financial stability. For instance, in October 2020, Mary Daly, president of the Federal Reserve Bank of San Francisco, stated in an interview[3]:

"We should always watch for excess risk-taking; we should always watch for excess leverage […] but we shouldn't regulate off the fear that could happen, and at the expense of so many millions of Americans who need the employment and the income and the access to the economy."

Nevertheless, the literature so far has not investigated whether systemic risk plays a role in the market reaction to monetary policy announcements. We address this question in this study by investigating the role of systemic risk in equity price reaction of financial institutions to changes in the short-term rates and the term structure.

The existing findings in the literature (that do not consider the institutions' systemic risk) is not sufficient to answer this question, as it is presumable that the effect of monetary policy differs across financial institutions with high systemic risk and those with low systemic risk. Conventional monetary policy measures might affect financial stability, but it is unclear whether and how they might affect the SIFIs under different economic environments. Tail risk in SIFIs can be absorbed by the government, and market expectations about government intervention might in turn influence bank stock prices. Gandhi and Lustig (2015) report that the largest US banks tend to have lower risk-adjusted returns than

[2] https://www.federalreserve.gov/newsevents/speech/brainard20200901a.htm

[3] https://www.ft.com/content/5c2b7d15-7e37-475a-8d42-1e8e0a3b8708

smaller banks because of such potential government intervention: ‘Too-Big-To-Fail’ (TBTF) institutions are considered safer by investors if a tail event becomes more likely at the macro level. Similarly, Abreu and Gulamhussen (2013) analyse the market reaction to the announcement of the list of TBTF banks by the Financial Stability Board in 2011 and find that the market perceives the TBTF label as value-enhancing. However, because of potential government guarantees, there might also be a correlation between sovereign debt risk and financial risk. For example, Correa et al. (2014) show that the largest financial institutions are hit more strongly by sovereign credit rating downgrades. Thus, monetary policy actions that are perceived to increase the risk of financial instability at the macroeconomic level might generate either a negative or a positive response within the financial institutions with high systemic risk, depending on which of these two effects is stronger.

While there are already contributions on the impact of monetary policy interventions on bank stocks (English, Van den Heuvel, and Zakrajšek 2018; Fiordelisi and Ricci 2016; Ricci 2015), these studies do not explicitly consider the impact of bank systemic risk on the price reaction to conventional monetary policy announcements. Fiordelisi and Ricci (2016) show that global systemically important banks (G-SIBs) respond well to monetary policy interventions during the crisis, but they do not estimate the price reaction for other (non-G-SIBs) banks. Therefore, it is unclear how unexpected changes in interest rates affect bank stock prices, and whether systemic risk plays any role in explaining heterogeneities in the price reaction. Ricci (2015) considers systemic risk at the country level and shows that banks in countries with higher systemic risk are more sensitive to expansionary measures. We contribute to this literature by including firm level systemic risk in our analysis. Furthermore, to have a larger and more heterogeneous sample, we focus on the entire financial system including banks and other financial institutions.

Our empirical strategy follows a portfolio time-series approach as well as a panel-data approach. In our portfolio time-series approach, we construct portfolios based on systemic risk index and examine whether these portfolios show a significant price reaction to the monetary policy announcements. We specifically focus on the Fed funds target rate announcements made by the Federal Open Market

Committee (FOMC) from 2000 to 2015. In our panel-data approach, first we estimate the individual price reaction of the US financial sector stocks to the FOMC announcements. We then investigate how the price reaction of each financial stock (in terms of abnormal returns) correlates with systemic risk.

In our analysis, we allow for expectations with respect to Fed funds target rates. A "Positive Surprise" implies a higher than expected rate announcement, regardless of whether it is a rate cut, a rate hike or an unchanged rate. Similarly, a "Negative Surprise' means that the announced rate is lower than expected, regardless of whether there is a change (hike or cut) in the target rate or not. We compute the surprise component of each target rate announcement based on the seminal approach introduced by Kuttner (2001) and Bernanke and Kuttner (2005). In addition to the 'surprise component' of the rate changes, we also focus on the yield curve. In particular we examine whether the flattening of the yield curve has an impact on the way the 'surprise component' and systemic risk affect the abnormal returns. By doing so, we test for potential state-dependence in the effect of the two variables. This state-dependence is likely to be significant because of the strong negative signal a flat yield curve conveys to the market.

Our main findings suggest that systemic risk plays a significant role in the reaction of financial stocks to monetary policy announcements. Our portfolio time-series regressions show that a portfolio that is long in high-systemic-risk and short in the low-systemic-risk financial institutions has significantly higher returns on the days related to the positive surprises. The results of panel-data regressions suggest that a positive surprise of 25 basis points reduce the cumulative abnormal returns (CARs) by about 16 basis points. However, systemic risk has a positive (negative) impact on CARs related to positive (negative) surprises, and thus it mitigates the negative impact of positive surprises on CARs. This result is confirmed when we run the regressions for the whole sample and add two interaction terms: one interaction term between our proxy for systemic risk and a dummy identifying positive surprises; and one interaction term between systemic risk and a dummy identifying a flattening yield curve. The results for these regressions show that both interaction terms have a positive impact on abnormal returns. Since positive surprises and a flat yield curve can both be considered as signals of a potential crisis, these results are consistent with a "TBTF hypothesis".

We also provide results that contribute to the literature on the reaction of financial stocks to conventional monetary policy announcements. In particular, we show that the overall reaction of the financial firms to monetary policy interventions is asymmetric and state-dependent. The overall reaction is stronger for negative surprises than for positive surprises, which indicates that the responses are asymmetric. However, the effect of the negative surprises on the abnormal returns changes: in non-crisis (crisis) periods investors react negatively (positively) to lower than expected rates. This suggests that the impact of a certain policy change on the financial institutions depends on the overall state of the economy. This state-dependence is also observed in a different form when interacting the surprise component with the slope of the yield curve: Positive surprises increase the abnormal returns, unless they are accompanied by a flattening yield curve. In other words, unexpected increases in interest rates that flatten the yield curve have a negative effect on abnormal returns. Consistent with Borio, Gambacorta, and Hofmann (2017) we also find that term spread has a positive impact on the abnormal returns. This means that financial institutions show a more positive response to interest rate announcements whenever the yield curve is steeper.

Our results (partly) corroborate those provided by English, Van den Heuvel, and Zakrajšek (2018), who find that bank stock returns react negatively to unexpected increases in the level[4] and the slope of the yield curve. Without interacting the surprise component and flattening yield curve, we also find similar results. When we include the interaction term however, we find that the negative impact of the surprise component (or the "level surprise") is only limited to the cases where yield curve is relatively flat.

[4] English et al. (2018) define the surprise component of the target rate announcements as the "level surprise" of the yield curve. In addition, they define the difference between long-term Treasury yields and the "level surprise" as the "slope surprise".

All the evidence from our analysis regarding the role of systemic risk are in line with our "TBTF hypothesis": higher than expected short-term rates (or a flattening yield curve), which plausibly impose a higher distress risk on the financial system, tend to be associated with a relatively better response from the financial institutions with high systemic risk. This occurs despite the fact that such institutions are likely to have stronger ties with the aggregate economy and thus might be more heavily affected by economic downturns. This implies that the market participants believe that the financial institutions with high systemic risk are more likely to be recused by the authorities in case a crisis breaks out.

The remainder of this paper is structured as follows. In the next section we review the literature on systemic risk measures and develop our hypotheses. Section **3** explains the data and the methodology employed. Section **4** describes the results from our analysis. Section **6** concludes.

2. Literature review and hypothesis development

2.1. Literature review on monetary policy and the stock market

2.1.1. General key findings

The interaction between monetary policy and the financial markets has been studied extensively in the finance literature. An important line of research investigates the effect of monetary policy on interest rates (see Cook and Hahn (1989), Thornton (1998), Kuttner (2001), Cochrane and Piazzesi (2002)). A second line of research, which is more relevant to this study, focuses on the impact of monetary policy on stock markets (the reverse relation has also been investigated on a handful of studies, e.g. Mishkin (2007) and D'Amico and Farka (2011)). A seminal paper in this area is the one by Thorbecke (1997), who investigates the effects of monetary policy changes on stock market returns using several methods, including Vector Autoregression (VAR) models and event study analysis. Thorbecke (1997) provides evidence that monetary policy, at least in the short-run, has significant effects on the economy. The results suggest that an expansionary monetary policy leads to an increase in the ex-post stock returns hence it can be treated as a risk factor[5] when pricing equities. Patelis (1997) using long and short term models, concludes that monetary policy is one of the significant predictors of stock returns.

In more recent studies, one of the seminal works concerning the response of equity markets to monetary policy is Bernanke and Kuttner (2005). The paper carries out a comprehensive analysis of the stock market's reaction to FOMC announcements and investigates the possible transmission channels that explain the observed reaction. The results suggest that a hypothetical 25-basis-point 'surprise' reduction in the federal funds target rate leads to around one percent increase in the stock market index, and the main channel through which monetary policy affects asset prices is the market's expected equity risk premium.

The salient feature of the approach employed by Bernanke and Kuttner (2005) is the focus on the "surprise" component of the monetary policy announcements, rather than the total change in the target rate. Consistent with the efficient market hypothesis (Fama 1970), the authors argue that the market is not likely to respond to the policy actions that are already anticipated. The study uses a methodology initially proposed by Kuttner (2001) to isolate the surprise component of the announced target. This method uses information from the Federal Funds futures contracts to derive the market's expectation about the upcoming target rates. The technique has subsequently been adopted by many other studies (e.g. Gurkaynak, Sack, and Swanson (2004); Boyd, Hu, and Jagannathan (2005); Andersen et al. (2007); Zebedee et al. (2008); Wongswan (2009); Chuliá, Martens, and Dijk (2010); Hausman and Wongswan (2011); Bredin, Hyde, and Reilly (2010)). Overall, the empirical evidence confirms that expected policy actions do not tend to have a significant impact on security prices.

Several studies suggest that the stock market reaction to monetary policy announcements could be asymmetric (Chen 2007; Chuliá, Martens, and Dijk 2010). Using high-frequency data for individual stocks included in the S&P100 index, Chuliá, Martens, and Dijk (2010) report that the market responds

[5] Risk factors in asset pricing models refer to the different sources of risk for which the investors require a premium. Such as equity risk premium which is included in CAPM, Fama-French three-factor model, Carhart four-factor model etc.

differently to negative and positive target rate surprises. Their results suggest that the market reaction (in terms of returns and volatility) to negative news is more severe than to positive news. This result could be due to the use of high-frequency data, hence in general the evidence for such asymmetric effects is scarce (Chuliá, Martens, and Dijk 2010). In another study concerning the possible asymmetric reaction of the stock market to monetary policy, Chen (2007) examines whether a certain type of policy intervention can have different effects on returns in bull and bear markets. This hypothesis is tested using a Markov Switching Model, which allows for state-dependent responses of the dependent variable, where the "state" variable follows a Markov process[6]. The results reveal that a contractionary monetary policy significantly lowers the stock returns in both bull and bear markets. Chen (2007) also shows that monetary policy has a stronger impact on the returns in a bearish market. Furthermore, a monetary tightening results in a higher probability of switching to a bear market regime which could cause the returns to stay low for longer period of time in addition to the immediate negative response.

2.1.2. Studies using high-frequency data

The use of high-frequency data has been implemented in several studies. The main rationale behind using intraday data is to eliminate the possible effect of other confounding events and news that could have occurred on the same day as the policy announcement. By analysing the event over a very narrow event window these studies try to capture the pure effect of the announced policy on the markets (D'Amico and Farka 2011). However, in some cases, such as announcements of unconventional monetary policies, the market may not react immediately. Due to the unconventional nature of the policies, market participants might need more time to fully process the news and evaluate the situation. Joyce and Tong (2012) evaluate the effects of Bank of England's first round of quantitative easing (QE) programme on the UK government bond (gilt) market using high frequency data. The results of the

[6] Introduced by Hamilton (1989), the Markov Switching Model is a popular non-linear time series model in the literature. The model involves different equations which characterise the time series' behaviour under different regimes. The model is able to switch between different structures (equations) using a mechanism which is controlled by an unobserved "state" variable. This variable follows a first-order Markov chain which is a memoryless stochastic process.

study indicate that the initial QE announcements took significantly longer to become fully incorporated into the gilt prices while the later announcements had their impact more quickly. This suggests that in case of unconventional monetary policies the market does not tend to react immediately, and the processing of information happens in a more gradual manner.

Zebedee et al. (2008) use intraday stock market data to examine the relation between S&P500 returns and the FOMC announcements. Consistent with Chuliá, Martens, and Dijk (2010) and the majority of studies based on daily data, their results also confirm a significant relationship between the surprise element of the monetary policy announcements and the stock returns. The study also provides evidence of the speed at which the market reacts, suggesting that a new equilibrium is reached within 15 minutes of the announcement.

D'Amico and Farka (2011) analyse the interactions between stock market and the Fed with special attention given to possible endogeneity and omitted variable issues. Endogeneity in this case can happen if the Fed reacts to stock market movements and if the causal relationship between the Fed and the market is not unidirectional. The omitted variable bias can occur if there is an exogenous factor that affects both the market and the Fed decisions simultaneously while it is excluded from the analysis. The study tries to overcome these potential issues by using a VAR model, which assumes endogeneity by default, along with high-frequency data. Like most of the other studies, their results also confirm that a tightening monetary policy lowers the stock returns. However, they also find significant evidence of the Fed responding the information signalled from the stock market.

Another important study that attempts to address the possible endogeneity between monetary policy and stock returns is Rigobon and Sack (2004). The paper introduces a heteroscedasticity-based estimator of monetary policy shocks which estimates the shocks under weaker assumptions compared to event study approach[7]. This study confirms that an increase in short-term interest rates has a negative

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[7] Event study assumes the shocks induced from monetary policy are strong enough to dominate all other shocks that might happen simultaneously.

impact on stock returns. The results of the heteroscedasticity-based estimator indicate that there is a modest bias in event-study estimates. However, in the case for equity prices this bias is not found to be significant, so the event-study approach seems reliable.

2.1.3. Studies focusing on market volatility

Other aspects of the financial markets have also been studied broadly in the monetary policy literature. Bomfim (2003) investigates changes in stock market volatility before and after FMOC announcements, using a Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. He finds evidence that market volatility is abnormally low on the days preceding scheduled FOMC announcements. Monetary policy announcements have a significant impact on market volatility, with the surprise component playing an important role in the magnitude of the reaction. Furthermore, a positive surprise (higher-than-expected target rate) is found to boost volatility more strongly compared to a negative surprise (lower-than-expected target rate). This study also adopts the Kuttner (2001) approach to estimate the surprise components of the announced target rates.

Nikkinen and Sahlström (2004) and Clements (2007) are two of the other research works concerning the effect of FOMC and macroeconomic news announcements on market volatility, focusing on implied volatility (the VIX[8]) rather than realised volatility. Their results indicate that the implied volatility rises on the days prior to the scheduled news releases and drops after the announcements.

2.1.4. Studies focusing on unconventional monetary policies and the financial crisis

A number of studies on the effects of monetary policy on the financial markets particularly focus on unconventional monetary policies, which were widely implemented during the recent global financial crisis and the sovereign debt crisis in Europe. Joyce and Tong (2012) investigate the response

[8] The Chicago Board Options Exchange Volatility Index, known as the VIX, is an index measuring the volatility implied by the 30-day call and put options on the S&P500 index.

of the UK's gilt market to the QE programme using high frequency data and they find that the market took varying time to respond to the policies with the initial announcement taking longer to be fully incorporated into the gilt yields. Steeley and Matyushkin (2015), using GARCH models, study the effects of QE on the volatility of the returns in the gilt market both during the overall period and on the specific days of the asset purchases. They find evidence of the stabilising impact of QE programme on the gilt market. Joyce et al. (2011) show that the implied volatility of the stock market in the UK dropped during the first phase of the QE programme concluding that the QE was successful in recovering market confidence. More broadly, Rogers, Scotti, and Wright (2014) examine the overall impact of QE on the bond yields, stock prices and exchange rates in multiple countries and find evidence of successful easing of financial conditions by the QE programme.

Because of the unusual situation during the global financial crisis and the unconventional nature of the monetary policy actions in this period, the evaluation of the consequences of these policy decisions has been the subject of some important studies. Since the starting point of the global financial crisis was failures in the financial system and as the financial and banking stocks are shown to be more interest-rate-sensitive than the others (Kim, Lee, and Wu 2013), studying the impact of monetary policy interventions on the financial system is of particular importance. In a seminal study, using event study analysis, Aït-Sahalia et al. (2012) evaluate whether the financial and macroeconomic policy actions during the financial crisis were successful in reducing the financial distress. They consider the credit and liquidity risk premia in the global interbank markets as the main indicator of the financial distress. This indicator is measured as the spread between London Interbank Offered Rates (Libor) and Overnight Index Swaps (OIS) for the U.S. dollar. Possible alternative measures of financial stability such as bank-specific Credit Default Swap (CDS) spreads, equity prices and option-implied volatility (the VIX) have also been analysed to examine the robustness of the results.

The results of Aït-Sahalia et al. (2012) shed light on some important aspects of the financial markets' response to monetary interventions during the crisis. An interesting finding is that the response of the market to the policy announcements differed significantly before and after the collapse of Lehman

Brothers. The paper argues that the global phase of the financial crisis began after the failure of Lehman Brothers, which revealed the *systemic nature* of the ongoing crisis. So, there could be a possibility that the more systemically risky banks react differently to certain policy interventions.

Further findings by Aït-Sahalia et al. (2012) suggest that interest rate cuts helped reduce the financial distress in the system by lowering the Libor-OIS spreads, with larger declines during the global phase of the crisis, whereas unconventional monetary policy announcements did not show a significant negative impact on the Libor-OIS spreads. However, controlling for the surprise component of the monetary announcements (using survey data, with an approach different from Kuttner (2001)) reduces the level of significance of the reactions, making them insignificant in some cases. The authors attribute this result to possible state dependency of the reactions to monetary news (McQueen and Roley 1993) and argue that in a crisis context, both expected and unexpected elements of policy announcements could have a key impact due to the high uncertainty.

According to Aït-Sahalia et al. (2012), along with interest rate cuts, bank recapitalisations were also considered by the market participants as positive promising steps toward stabilising the system. On the other hand, ad hoc bank bailouts were found to cause an exacerbation of the markets concerns about future financial stability (similar to bank failures). Using alternative measures of financial stability also leads to similar conclusions.

2.1.5. Studies focusing on the financial sector

As explained earlier, studying the reaction of the financial and banking sector to monetary policy changes is particularly important for various reasons. On this topic, Ricci (2015) looks at the stock market reaction of large European banks to both conventional and unconventional monetary policy decisions adopted during the financial crisis. Furthermore, the study also tests which bank-specific factors determine the banks' reaction to the policy news. This is one of the few studies on the effects of monetary policy that particularly focuses on banking sector, analysing data at bank level, in a similar approach to ours.

Using event study approach, Ricci (2015) analyses the effects of 490 monetary policy announcements during the subprime and global phases of the financial crisis (according to definitions used by Aït-Sahalia et al. (2012)) and the sovereign debt crisis in Europe. In the second stage of the analysis the paper investigates whether there is a relationship between the reaction of the stock prices (CARs on the announcement dates) and the following bank-specific variables: capital ratio, liquidity ratio, idiosyncratic risk (risk-weighted assets over total assets), systemic risk (country specific banking system ranking issued by the Economic Intelligence Unit).

Consistent with Fiordelisi, Galloppo, and Ricci (2014), the findings by Ricci (2015) also suggest that the banks' stock returns were more sensitive to the unconventional monetary measures rather than conventional interest rate decisions. This is while according to the study by Aït-Sahalia et al. (2012) unconventional monetary policy announcements did not cause a significant movement in the Libor-OIS spreads. This could be considered as an evidence that compared to the interbank lending market, the stock market reacts more quickly to unconventional monetary interventions. However both papers find evidence supporting the view that the markets' reaction to a certain policy action could be different depending on the stage of the crisis (i.e. the reaction seems to be state dependent (McQueen and Roley 1993)). Moreover, the results of both studies demonstrate cross-country spillover effects of monetary policy.

The results from the second stage of Ricci (2015) are as follows: banks with higher liquidity and Tier 1 capital ratio (i.e. stronger balance sheets) are less sensitive to monetary policy announcements. The idiosyncratic risk measure used (risk weighted asset ratio) does not capture any significant effect on the level of CARs. The *systemic risk* measure in the model, however, is found to have a significant impact on the reaction of the bank stocks. The banks operating in countries where the financial system is considered more systemically risky show a greater response to monetary policy announcements (benefit more from expansionary and lose more from tightening policy decisions). To the best of our knowledge, this is the only existing research work that draws a direct link between the systemic risk of a financial firm and its reaction to monetary policy interventions.

In another important study, Fiordelisi and Ricci (2016), using event study analysis, carry out a broad assessment of various policy actions taken during the financial crisis across different countries focusing on Global Systemically Important Banks (G-SIBs). Their assessment of the policies' effectiveness is based on the impact of the policy on the stock return and the CDS spreads of the sample banks. A group of non-financial companies are also observed as a control group. The results demonstrate a very wide heterogeneity among the reaction of the banks across different regions and for different policy interventions. This heterogeneity seems to be beyond the different reaction Aït-Sahalia et al. (2012) and Ricci (2015) observed for the similar policies occurring in different stages of the crisis. Another interesting finding in the study is that banking stocks benefit from monetary policy changes regardless of the direction of the policy (expansionary or contractionary); a result which does not hold for non-financial firms. Hence it seems that the markets general perception is that during crisis times, monetary policy interventions are mostly in favour of banks rather than the other sectors. Bank failures and bailouts, however, are found to have a significant negative impact on both financial and non-financial firms.

The results of Fiordelisi and Ricci (2016) also suggest that in spite of the global character of the G-SIBs, the banks are still more sensitive to the policy decision made at their own currency area. Similar results have been observed for international bond markets (Bredin, Hyde, and Reilly 2010). Unlike Ricci (2015), the study of Fiordelisi and Ricci (2016) does not try to identify the possible bank-specific determinants of each bank's reaction to the policy news. Although the banks under study are the G-SIBs (as released by the Financial Stability Board (FSB) on November 4, 2011 and then updated in November 2012), it is not tested whether systemic risk is a key determinant of the bank's reaction to monetary policy decisions and whether banks with higher or lower systemic risk are more or less sensitive to the policies.

There are a few other studies that particularly focus on banking stocks while investigating the possible effects of monetary policy interventions. Madura and Schnusenberg (2000) analyse how changes in the federal funds target rate affect the commercial bank stock returns for the period 1974-

1996. They find that a decrease in the target short-term interest rates significantly boosts bank equity returns, however the reverse does not hold for target rate rises (i.e. the reaction of the banks' stock returns are asymmetric). The study by Yin, Yang, and Handorf (2010), also confirms the negative relationship between the Federal funds target rate and bank stock returns, providing evidence that banking stocks react only to the surprise component of the target rate changes. They also show that the reaction of banking stocks to the FOMC target rate decisions is state-dependent and it depends on the context in which the policy takes place (similar to Aït-Sahalia et al. (2012) and Ricci (2015)). More recent studies also suggest that there is a negative relationship between banking sector returns and interest rates (Altavilla, Boucinha, and Peydró 2018; English, Van den Heuvel, and Zakrajšek 2018). This finding is not conclusive however and there are studies that find the relation to be the opposite, mixed or insignificant (Alessandri and Nelson 2015; Borio, Gambacorta, and Hofmann 2017; Fiordelisi, Galloppo, and Ricci 2014).

The results of Madura and Schnusenberg (2000) also suggest that smaller and better-capitalised banks (consistent with Ricci (2015)) are less sensitive to the monetary policy changes. The study does not consider any risk-related factor as a possible determinant of the banks' sensitivity to the Fed's policy actions. Funding sources of the banks (deposit vs. non-deposit) are also found to be significant determinants of the banking stocks' reaction to the Federal funds target rate changes in a study focusing on pre-crisis period (Yin and Yang 2013). Banks relying more on non-deposit sources are found to be more exposed to monetary shocks.

In another study focusing on bank liquidity regulation instead of monetary policy announcements, Onali, Schaeck, and Bruno (2016) document a somewhat different set of bank- and country- specific characteristics that determine the reaction of the bank equity prices to the mentioned regulatory announcements. They find that higher liquidity and higher charter value (proxied by market-to-book ratio and the ratio of customer deposits to total assets) have a positive impact on the abnormal returns of the banks on the announcement days. Exposure of the bank to funding mismatch is also found to reduce the negative reaction of the stock prices. Furthermore, some country-specific characteristics are also found to have a significant role in the banks' stock market reaction. For instance, banks located in countries with higher government debt and tighter interbank conditions are found to be more sensitive to the liquidity regulation announcements.

2.2. Introducing systemic risk and hypothesis development

2.2.1. Financial crises and systemic risk

Empirical studies show that the most severe stages of the financial crisis started after the failure of Lehman Brothers on September 15, 2008 (Acharya, Engle, and Richardson 2012). The Lehman's collapse demonstrates that failure of large financial institutions can have a broad impact on the rest of the finance industry and, ultimately, on the entire economy. The severity of this impact, which depends on the degree of correlation between the value of a financial firm and that of the financial system as a whole, is known as the systemic risk of the firm. Federal Reserve governor Daniel Tarullo defines SIFIs as:

"Financial institutions are systemically important if the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy (Acharya, Engle, and Richardson 2012)."

Because of the detrimental effect of the financial crisis, and since the conventional measures of idiosyncratic risk such as Value at Risk are not sufficient to capture the systemic risk of the firm (Adrian and Brunnermeier 2016), correctly measuring systemic risk has become an important concern for finance academics and practitioners. Many of the current financial regulations aiming to reduce systemic risk, such as Basel capital requirements, are actually targeting the idiosyncratic risk of the individual financial firms. As a result, such regulations may not be able to mitigate the level of risk in the financial system as a whole (Acharya et al. 2017).

A key objective of the post-crisis literature is to introduce a quantifiable measure of systemic risk that can be useful to both the regulators and financial institutions' managers. For example, Adrian and Brunnermeier (2016) introduce the ΔCoVaR, which is designed to capture the tail risk dependency between the firm and the financial system and can be estimated using quantile regressions. Out-of-sample forecasts show that the 2006Q4 value of the forward looking ΔCoVaR would have predicted a significant fraction of the realised ΔCoVaR during the financial crisis of 2007-2009 (Adrian and Brunnermeier 2016).

Acharya et al. (2017) provide a framework to estimate the expected contribution of a financial institution to a systemic failure, that is, the amount of capital shortfall the firm would face when the aggregate capital in the system drops below a certain threshold. This measure is called Systemic Expected Shortfall (SES) and estimates the propensity of an institution to be undercapitalised when the whole system is undercapitalised. This approach takes an opposite perspective with respect to CoVaR: SES estimates the loss of the firm conditional on a systemic loss, whereas CoVaR calculates the loss of the system conditional on the loss of the firm.

For a generic firm, i , SES is defined as the amount by which the equity value of the firm, ω, goes below a "required" threshold, defined as the fraction, τ, of its total assets, a, when the aggregate equity capital in the banking system, W, is below τ times the aggregate amount of assets in the banking system, A:

$$SES^i \equiv E\left[\tau a^i - \omega^i \,\middle|\, W < \tau A\right] \quad (1)$$

This model has important policy implications: financial institutions should be taxed based on their SES, which can be considered as the system-wide externality of their risk-taking strategies. Leverage and Marginal Expected Shortfall (MES) of a firm (i.e. the expected net equity return of the firm conditional on a moderate tail shock to the aggregate market) are strong determinants of the SES (Acharya et al. 2017).

Acharya, Engle, and Richardson (2012) develop the original model introduced by Acharya et al. (2017), which was distributed as a working paper in 2010, to introduce a methodology for estimating systemic risk based on a similar approach to SES. By introducing the "SRISK" index, this methodology captures determinants of systemic risk, such as size, leverage and the time-varying correlation between the firm's stock returns and the market. *SRISK* for a generic financial institution, *i*, can be defined as:

$$SRISK_{i,t} = E_{t-1}(Capital\ Shortfall_i\ |Crisis) \tag{2}$$

Assuming a prudential capital ratio of k (typically equal to 8%), the equation can be further expanded as:

$$\begin{aligned} SRISK_{i,t} &= E\big((k(Debt + Equity) - Equity) \mid Crisis\big) \\ &= kDebt_{i,t} - (1-k)\big(1 - LRMES_{i,t}\big) \times Equity_{i,t} \end{aligned} \tag{3}$$

The model is based on a six-month forecasting horizon and it assumes that the book value of debt remains approximately unchanged during this period and under a crisis scenario. The variable *LRMES* (Long-Run Marginal Expected Shortfall) measures the factional loss of the equity value of the firm if a crisis happens. *LRMES* is calculated as[9]:

$$LRMES_{i,t} = 1 - exp(log(1-d) \times \beta_{i,t}) \tag{4}$$

Where d is the assumed six-month crisis threshold for the market (40% by default) and β is the market beta of the firm which is estimated using a combination of the constant and time-varying betas. More specifically the "nested beta" is estimated using the following equation:

$$r_{i,t} = (\emptyset_1 + \emptyset_2\beta_{i,t})r_{m,t} + \sqrt{h_{i,t}}\xi_{i,t} \tag{5}$$

Where $r_{i,t}$ and $r_{m,t}$ are the firm and the market returns, $\beta_{i,t}$ is the time-varying beta and $\big(\emptyset_1 + \emptyset_2\beta_{i,t}\big)$ is the nested beta which combines the time-varying and constant betas. The error terms are assumed to be a GJR-GARCH(1, 1) with the conditional heteroscedasticity $h_{i,t}$ and the innovation term $\xi_{i,t}$.

[9] For further details on SRISK estimation refer to the V-Lab's website: https://vlab.stern.nyu.edu.

The *SRISK* approach has received a high level of attention in the literature,[10] and researchers have provided extensions and empirical applications (Brownlees and Engle 2016). The main advantage of *SRISK* relative to the CoVaR approach is that *SRISK* takes into account the stock return volatility of the firm as well, whereas CoVaR is based merely on correlation and it treats two stocks with different volatilities the same (Acharya, Engle, and Richardson 2012)[11].

This paper adopts the *SRISK* approach to analyse the possible links between systemic risk and monetary policy decisions. This is because *SRISK* is an easily quantifiable and comprehensive measure.

2.2.2. Interest rates, term structure and systemic risk

A priori, it is hard to predict how the financial sector reacts to interest rate decisions. Higher interest rates can result in higher net interest margin for financial institutions (especially for depository institutions), because the sensitivity of deposit rates to changes in interest rates might be lower than that of loan rates (Heider, Saidi, and Schepens 2019). However, higher interest rates might also reduce the demand for credit from businesses and households and increase the cost of capital for financial institutions, which might lead to a lower charter value.

The empirical evidence on the response of the financial institutions to monetary policy decisions is also mixed. Recent studies suggest that banks tend to react negatively to higher interest rates (Altavilla, Boucinha, and Peydró 2018; English, Van den Heuvel, and Zakrajšek 2018). Therefore, it seems that the positive impact of interest rate hikes on the net interest margin is not sufficient to compensate the negative impact of a higher cost of capital on charter value. This suggests that financial stocks react to the conventional monetary policy decisions in a similar manner as the rest of the market (Bernanke and Kuttner 2005). Other studies, however, find mixed results about the response of financial stocks to

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[10] The Volatility institute (V-Lab) of NYU Stern School of Business provides rankings and analysis based on (Acharya, Engle, and Richardson 2012) for the US and global financial institutions.

[11] A few other approaches to analyse systemic risk have also been expanding in the recent years. These include network and financial contagion analyses discussed by Minoiu and Reyes (2013) and Elliott, Golub, and Jackson (2014).

monetary policy decisions (Alessandri and Nelson 2015; Borio, Gambacorta, and Hofmann 2017; Fiordelisi, Galloppo, and Ricci 2014; Fiordelisi and Ricci 2016; Ricci 2015). By analysing the effect of unexpected changes in interest rates (or in the yield curve) on the abnormal returns of financial stocks we also contribute to the literature on the impact of monetary policy decisions on the financial sector.

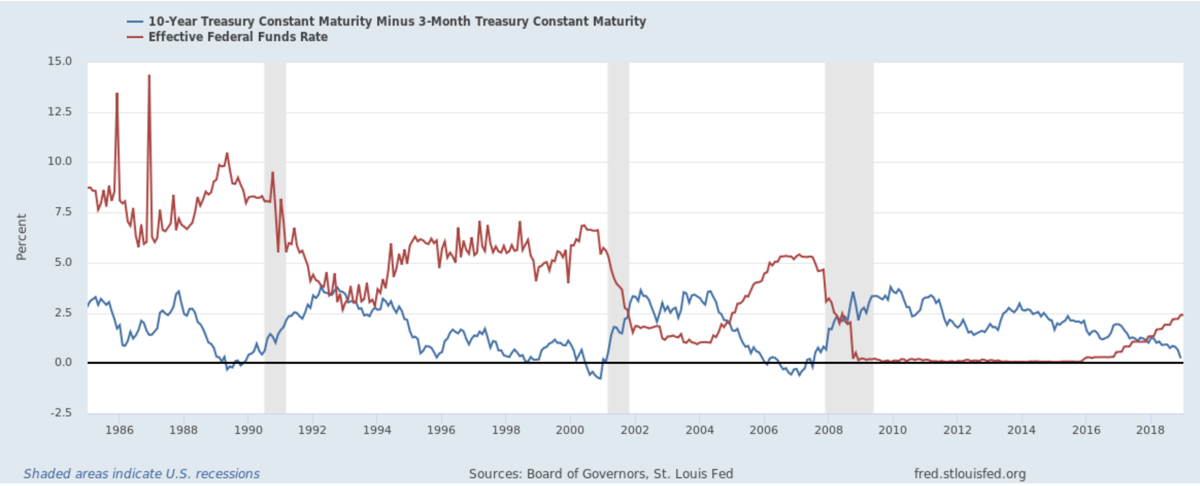
To develop our hypotheses on the role played by systemic risk in the financial stocks' price reaction to conventional monetary measures, we focus on the role of unexpected changes in interest rates. Unexpected rises in the short-term interest rates are likely to increase the distress risk within the financial system, for two reasons.

First, as shown in ***Figure 1***, rises in the Fed funds effective rate have usually been associated with flattening of the yield curve, and a flattening yield curve is commonly regarded as a strong signal of an upcoming recession. All the NBER recessions since 1964 except for one case have been preceded by an inverted yield curve (Ang, Piazzesi, and Wei 2006). Several studies have documented the predictive power of the yield curve with respect to recessions (Ang, Piazzesi, and Wei 2006; Chauvet and Potter 2005; Estrella 2005; Estrella and Mishkin 1998; Rudebusch and Williams 2009; Wright 2006). Nevertheless, it is not only the term spread that contains information about future recessions and slowdown periods. Ang, Piazzesi, and Wei (2006) show that the nominal short-term rate has in fact a higher predictive power than any term spread when forecasting future GDP growth. Their findings indicate a strong negative relation between the short-term rates and future GDP growth. We therefore mainly focus on the short-term rates in this study, although we also include the term spread.

Second, higher short-term rates and a flatter yield curve can also dampen the earnings of the financial institutions who borrow short-term and lend long-term, generating a negative price reaction for financial stocks. Recent contributions suggest that overall the relation between the short-term interest rates and bank stock returns is negative (Altavilla, Boucinha, and Peydró 2018; English, Van den Heuvel, and Zakrajšek 2018). Although Altavilla, Boucinha, and Peydró (2018) show that this negative relation does not hold anymore when they control for the endogeneity of the policy measures to expected macroeconomic and financial conditions. Also, the study by English, Van den Heuvel, and

Zakrajšek (2018) does not consider the crisis and post-crisis periods so their sample period does not perfectly overlap with ours. There is also evidence that a steeper yield curve boosts bank profitability (Borio, Gambacorta, and Hofmann 2017).

Figure 1 – Effective federal funds rate Vs the term spread



Notes: The graph draws comparison between the effective federal funds rate (red line) and the slope of the yield curve (blue line) from 1985 until the end of 2018. The effective Federal funds rate is the rate depository institutions charge each other for overnight lending. The slope of the yield curve is measured by the term spread between the 3-month and 10-year Treasury bill yields. The shaded areas indicate the NBER recession periods. The graph indicates that an inverted yield curve has regularly been followed by a recession period.

Nevertheless, as explained earlier, there is not a conclusive consensus among the prior findings regarding the effect of the interest rates and the yield curve on the financial sector, although most of the findings are pointing at negative consequences of a flattening yield curve. Because of the current low-interest rate environment, the predictive power of the yield curve and its relationship with recessions has been subject to debate in the recent studies (see, for instance: Bordo and Haubrich 2020; De Backer, Deroose, and Van Nieuwenhuyze 2019). There is evidence that the yield curve might be reflecting an exaggerated risk of an upcoming recession in the post-crisis period, as the short-term rates have almost reached zero and the yield curve slope is mainly dominated by the long-term rates (Cooper, Fuhrer, and Olivei 2020).

The studies that investigate the relationship between the interest rates and the banking and finance sector (e.g., English, Van den Heuvel, and Zakrajšek (2018)) usually have a different sample period than ours. Overall, the existing evidence is slightly more in favour of the view that considers rate hikes bad news for the financial sector, but since this relationship is very likely to be state-dependent, we mainly rely on our own empirical results when making assumptions in this regard. Therefore, as shown in section 4.2, our main assumption s is that higher short-term rates are considered bad news for financial stocks.

Since high interest rates are associated with an increased likelihood of an upcoming systemic distress, investors might prefer TBTF institutions whenever the announced interest rates are unexpectedly high. This is because the TBTF institutions are considered to be less exposed to tail risk (Gandhi and Lustig 2015). For this reason, the main hypothesis tested in this paper is:

TBTF hypothesis: Financial institutions with high systemic risk react better than those with low systemic risk to unexpected increases in short-term interest rates.

It might be argued that a higher systemic risk implies a stronger relationship between the performance of an individual institution and that of the aggregate economy (Correa et al. 2014). Moreover, higher short-term interest rates usually constrain macroeconomic growth. If this is true, the *TBTF hypothesis* may not be supported in real financial markets. For this reason, we also test an alternative hypothesis.

Macroeconomic contraction hypothesis: Financial institutions with high systemic risk react worse than those with low systemic risk to unexpected increases in short-term interest rate.

This hypothesis implies that the stock market does not necessarily believe that the TBTF institutions are guaranteed to be rescued (that is, the “TBTF hypothesis” is invalid).

3. Data and methodology

3.1. Data description

We collect daily stock returns of 95 systemically risky financial institutions for the period 01/01/2000 – 31/12/2015 from the CRSP database [12] and information about Fed Funds target rates decisions (147 FOMC announcements)[13] from the Federal Reserve's website. Our sample period ends in conjunction with the end of the zero-lower-bound (ZLB) period. The Fed announced its first rate hike after the crisis on 16/12/2015 increasing the lower bound from zero to 25 basis points. We exclude two announcements from our analysis because of significant confounding events:[14] the announcement that took place on September 17, 2001, because of the proximity to the 9/11 terrorist attacks; and the announcement released on 16/09/2008, because it was one day after the collapse of Lehman Brothers. Also, as the interest rates were reduced to nearly zero and unconventional monetary policies were introduced following the financial crisis, we run our model controlling for the ZLB period as a robustness test presented in Appendix **5**. Another remarkable event within our sample period is introduction of the Troubled Asset Relief Programme (TARP) in response to the financial crisis. However, there are no TARP-related events that exactly confound with our event dates.

Daily values of the *SRISK* index for all the financial institutions in our sample are provided by the Volatility Lab of NYU Stern[15]. Finally, we collect financial data for our control variables from the COMPUSTAT database.

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[12] The list of the financial institutions as well as a comparison between our sample financial institutions and the total US financial sector in terms of market capitalisation are provided in Appendix **1**.

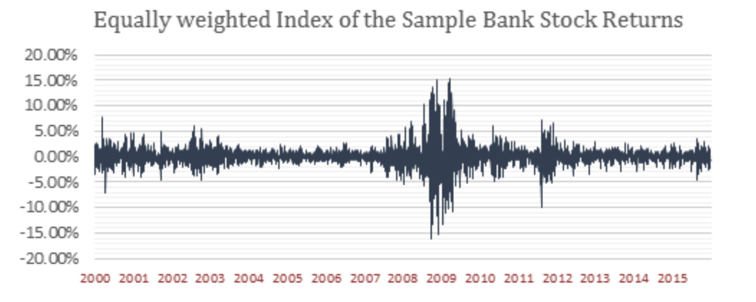
[13] The table in Appendix **2** provides a summary of 147 FOMC announcements of the Fed funds target rate under examination. The announcements include 22 rate cuts, 19 rate hikes and 108 unchanged policy (no target rate change) announcements.

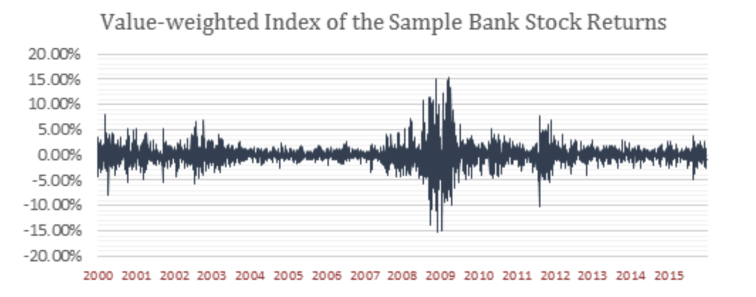
[14] Details of the announcements can be found in Appendix **2**.

[15] We only consider financial institutions for which data is available during the sample period from the V-lab's website. There is a large variation in SRISK values within our sample firms (from highly positive to highly negative). We also estimate SRISK for the other US financial institutions for which data is unavailable from V-lab. However, for the majority of these institutions SRISK is close to zero for the sample period under investigation.

We employ equally-weighted and value-weighted indices of the 95 financial institutions in the sample to carry out analysis on the overall reaction of the financial sector to the FOMC announcements**.** **Figure 2** shows the returns of the two indices over the sample period and **Table 1** reports the main descriptive statistics for the returns of the two indices.

Figure 2 - Time series plots of the equally-weighted and value-weighted indices of daily stock returns for a sample of 95 financial stocks.





Notes: The graphs show the daily returns of the equally-weighted and value-weighted portfolios of the sample financial institutions. The sameple covers the period from 01/01/2000 to 31/12/2015. The equally-weighted portfolio is constructed by calculating the daily means of the sample stock returns. The value-weighted index is built by calculating the daily weighted average (based on market cap) of the stock returns.

Table 1 - Summary statistics of the sample stock returns

	Equally-weighted portfolio	*Value-weighted portfolio*
Mean	0.00059	0.00032
Median	0.00068	0.00036
Standard Deviation	0.01897	0.01888
Kurtosis	13.55970	12.31132
Skewness	0.25794	0.28545
Minimum	-0.16105	-0.15219
Maximum	0.15284	0.15519
Count	4025	4025

Notes: The table presents summary statistics of the two portfolios constructed by the sample firms. The equally-weighted portfolio is constructed by calculating the daily means of the sample stock returns. The value-weighted index is built by calculating the daily weighted average (based on market cap) of the stock returns.

In addition to the equally-weighted and value-weighted indices of the sample firms, we also construct two portfolios based on the systemic risk of the firms: a "H-*SRISK*" portfolio, consisting of the firms that are in the top 20th percentile of the distribution of *SRISK* in the previous quarter; and a "L-*SRISK*" portfolio, comprising the firms in the bottom 20 percentile of the distribution. The portfolio weights are rebalanced quarterly. We run tests on these portfolios in the remainder of this paper.

3.2. Econometric methodology

Event studies are commonly employed to address research questions similar to ours (see for instance: Girotra, Terwiesch, and Ulrich 2007; Correa et al. 2014; Ricci 2015; Fiordelisi and Ricci 2016; Bruno, Onali, and Schaeck 2018). Although event studies focus on the short-term effects of an event (policy decisions in this case) on a firm or the market, such short-term effects could be indicative of the long-term impact of the policy (Aït-Sahalia et al. 2012).

We borrow from recent literature for the implementation of our event study, and in particular from Bruno, Onali, and Schaeck (2018). The first stage of our analysis requires estimation of the CARs and cumulative market-adjusted returns (CMARs) of the sample banks on the days of FOMC announcements. The second stage of the analysis involves portfolio time-series regressions and panel data regressions to investigate the impact of systemic risk on the price reaction to monetary policy events.

In the first stage, we regress the daily returns of the constructed portfolios on daily market returns, while two dummy variables control for the days of positive surprise and negative surprise FOMC announcements: in particular, $PositiveSurp_t$ is equal to 1 on days with a "Positive Surprise" and zero otherwise, and $NegativeSurp_t$ takes the value 1 on days with a "Negative Surprise" and zero otherwise.

In second stage, the estimated CARs and CMARs are regressed on *SRISK* and a set of control variables using a random effects model with fixed year effects.

3.2.1. Estimation of CARs and CMARs

The market model (or minor modifications thereof) is the most common technique to estimate Cumulative Abnormal Returns (CARs) in event studies (for example, Bruno, Onali, and Schaeck

(2018)). Cable and Holland (1999) show that the market model performs better than the CAPM and other models. The abnormal return on each day is estimated as follows:

$$AR_{i,t} = R_{i,t} - (\alpha + \beta R_{m,t}) \tag{6}$$

The variable $AR_{i,t}$ refers to the abnormal return of firm i on the day t. $R_{i,t}$ and $R_{m,t}$ are the day t returns of the firm and the proxy for the market portfolio, respectively.

The market-adjusted return is simply the difference between $R_{i,t}$ and $R_{m,t}$:

$$MAR_{i,t} = R_{i,t} - R_{m,t} \tag{7}$$

For a given event window (t_1, t_2), the CARs and CMARs are:

$$CAR_{i,t} = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{8}$$

$$CMAR_{i,t} = \sum_{t=t_1}^{t_2} MAR_{i,t} \tag{9}$$

Consistent with the previous work (Bruno, Onali, and Schaeck 2018; Fiordelisi and Ricci 2016; Ricci 2015) we employ a 260 trading-day estimation window which starts 264 days prior to the event and ends 5 days before the event (-264, -5) to estimate α and β.

Similar to Aït-Sahalia et al. (2012) and Ricci (2015) we use the following event windows: (-1, +3), (-1, +1) and (0, 0). We use the CRSP value-weighted index as a proxy for the market portfolio (Bernanke and Kuttner 2005).

We test for the significance of the mean 3-day CARs on each event day using the adjusted Boehmer, Masumeci, and Poulsen (1991) test statistic (ADJ-BMP) proposed by Kolari and Pynnönen (2010) which is also used by Ricci (2015). To calculate the ADJ-BMP statistic first we need to standardise the CARs for each individual firm on each event day:

$$SR_i = \frac{CAR_i(t_1, t_2)}{\hat{\sigma}_{\varepsilon_i}\sqrt{T_{ev} + \frac{T_{ev}^2}{T} + \frac{\sum_{t=t_1}^{t_2}[R_{Mt} - T_{ev}(\bar{R}_M)]^2}{\sum_{t=t_1}^{t_2}(R_{Mt} - \bar{R}_M)^2}}} \tag{10}$$

where $CAR_i(t_1, t_2)$ is the cumulative abnormal returns for firm *i* over the event window (t_1, t_2). $\hat{\sigma}_{\varepsilon_i}$ is the standard deviation of the estimated abnormal returns (i.e. residuals) over the estimation window. T_{ev} is the event window length and *T* is the estimation window length; R_M is the return of the market portfolio and $\bar{R}_M$ is the mean market return during the estimation period. The Z statistic (with a *t* distribution and *T-2* degrees of freedom and converging to a unit normal) is obtained as follows:

$$Z = \frac{\frac{1}{N}\sum_{i=1}^{N} SR_i}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(SR_i - \sum_{i=1}^{N}\frac{SR_i}{N})^2}} \tag{11}$$

where *N* is the number of firms considered on each event. The ADJ-BMP statistic is calculated by multiplying the above Z statistic by an adjustment factor as follows:

$$\text{ADJ-BMP} = \frac{\frac{1}{N}\sum_{i=1}^{N} SR_i}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(SR_i - \sum_{i=1}^{N}\frac{SR_i}{N})^2}} \cdot \sqrt{\frac{1-\bar{r}}{1+(N-1)\bar{r}}} \tag{12}$$

where $\bar{r}$ is the average of the cross-correlations of the estimated residuals of the sample firms in the estimation period. In other words, $\bar{r}$ is the average of the upper triangle elements in the correlation matrix of the estimation period residuals of the firms in the sample.

In addition to the ADJ-BMP statistic, we also calculate the bootstrapped *p-values* to determine the significance of the estimated average CARs and CMARs over different subsamples of the events (e.g. positive surprises, negative surprises, crisis period etc.). For this purpose, first we exclude all the days around the actual events, using a (-1, +1) event window, from the sample. Then, we randomly choose placebo events from the remaining trading days. The size of the placebo sample is equal to the size of the sub-sample being tested (e.g. positive surprises, negative surprises etc.). Finally, we estimate the placebo CARs and CMARs, based on the placebo sample of event days and generate an average CAR or CMAR in each simulation. This process is repeated 1,000 times to build a simulated distribution of randomly selected placebo average CARs and CMARs. This allows us to generate critical values for two-tailed statistical tests and compute the significance level at which the estimated CARs and CMARs differ from zero.

3.2.2. Systemic risk and price reaction to monetary policy announcements

We use two approaches to estimate the impact of systemic risk on the price reaction of our 95 financial stocks to FOMC announcements.

First, in a similar vein as Berkman, Cole, and Fu (2010) we run portfolio time series regressions. We regress the daily returns of three different portfolios on two dummy variables indicating the days of positive surprise and negative surprise announcements, controlling for the proxy for the market portfolio.

The three portfolios are: 1) a portfolio that is long in the H-*SRISK* portfolio and short in the L-*SRISK* portfolio; 2) The equally-weighted portfolio of the 95 financial stocks in our sample; 3) The value-weighted portfolio of the 95 financial stocks in our sample. The purpose of these regressions is to see whether the H-*SRISK* portfolio responds to a stronger extent to unexpected interest rate changes than the other portfolios. We run the following models:

$$R(H\_SRISK_t) - R(L\_SRISK_t) = \alpha + \beta_1 CRSPVW_t + \beta_2 PositiveSurp_t + \beta_3 NegativeSurp_t + \varepsilon_t \tag{13}$$

$$R(EW_t) = \alpha + \beta_1 CRSPVW_t + \beta_2 PositiveSurp_t + \beta_3 NegativeSurp_t + \varepsilon_t \tag{14}$$

$$R(VW_t) = \alpha + \beta_1 CRSPVW_t + \beta_2 PositiveSurp_t + \beta_3 NegativeSurp_t + \varepsilon_t \tag{15}$$

where $R(H\_SRISK_t)$, $R(L\_SRISK_t)$, $R(EW_t)$ and $R(VW_t)$ denote the daily returns of the H-*SRISK*, L-*SRISK*, equally-weighted and value-weighted portfolios respectively. $CRSPVW_t$ is the daily returns of the CRSP value-weighted index.

Our second approach is based on regressing the CARs and CMARs of each firm in our sample on *SRISK* and other control variables. We run the regressions on three different subsamples: 1) A subsample considering only announcements with a positive surprise component; 2) A sub-sample for the announcements with a negative surprise component; 3) A sub-sample for the announcements with a zero surprise component. In all cases, we employ a random effects model, because a fixed-effect model would eliminate time-invariant regressors from the analysis (Bruno, Onali, and Schaeck 2018). We also control for year fixed effects, with heteroscedasticity-robust standard errors clustered at the firm level:

$$CAR_{i,t} = \alpha + \beta_1 SRISK_{i,t} + +\varepsilon_{i,t} \tag{16}$$

$$CAR_{i,t} = \alpha + \beta_1 SRISK_{i,t} + \beta_2 Market\_Cap_{i,t} + \beta_3 MtB_{i,t} + \theta_1 Rate\_Cut_t + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_t + \gamma_2 Global_t + \gamma_3 PostCrisis_t + \lambda FirmType_i + \varepsilon_{i,t} \tag{17}$$

$$CMAR_{i,t} = \alpha + \beta_1 SRISK_{i,t} + \varepsilon_{i,t} \tag{18}$$

$$CMAR_{i,t} = \alpha + \beta_1 SRISK_{i,t} + \beta_2 Market\_Cap_{i,t} + \beta_3 MtB_{i,t} + \theta_1 Rate\_Cut_t + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_t + \gamma_2 Global_t + \gamma_3 PostCrisis_t + \lambda FirmType_i + \varepsilon_{i,t} \tag{19}$$

In addition to the regressions above, we also run regressions controlling for the surprise change in the target interest rates (*SurpComp*) without sample splits:

$$\begin{aligned} CAR_{i,t} = {} & \alpha + \beta_1 SRISK_{i,t} + \beta_2 Market\_Cap_{i,t} + \beta_3 MtB_{i,t} + \beta_4 SurpComp_t + \theta_1 Rate\_Cut_t \\ & + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_t + \gamma_2 Global_t + \gamma_3 PostCrisis_t \\ & + \lambda FirmType_i + \varepsilon_{i,t} \end{aligned} \tag{20}$$

$$\begin{aligned} CMAR_{i,t} = {} & \alpha + \beta_1 SRISK_{i,t} + \beta_2 Market\_Cap_{i,t} + \beta_3 MtB_{i,t} + \beta_4 SurpComp_t \\ & + \theta_1 Rate\_Cut_t + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_t + \gamma_2 Global_t \\ & + \gamma_3 PostCrisis_t + \lambda FirmType_i + \varepsilon_{i,t} \end{aligned} \tag{21}$$

The variable $CAR_{i,t}$ refers to the CAR of firm *i* at the event on date *t. $SRISK_{i,t}$* is the systemic risk index for firm *i* on the event day *t.* The two variables, *Market_Cap* and *MtB* refer to the market capitalisation and market-to-book ratio of the firms. The variables *Rate_Cut* and *Rate_Hike* are dummy variables, which are equal to one if the announced policy is a rate cut or a rate hike respectively and zero otherwise.

The dummy variables *Subprime, Global* and *PostCrisis* control for the subprime and global phases of the financial crisis as well as the post-crisis period. The specific periods for each of the subprime and global phases of the crisis are consistent with the dates used by Aït-Sahalia et al. (2012). The period from 01/06/2007 until 14/09/2008 (the day before the collapse of Lehman Brothers) is considered as the "subprime crisis phase": *Subprime* is equal to one during the period and zero otherwise. *Global* takes on the value one during the "global phase" of the crisis, which runs from the 15/09/2008 to the 31/03/2009, and zero otherwise. The end of the crisis is two days before the G20 Leaders' Summit on Financial Markets and the World Economy held in London, where global leaders made commitments to rescue the global financial system by providing considerable amounts of liquidity. *PostCrisis* is equal to one for the period from 01/04/2009 until end of the sample period, and zero otherwise.

FirmType is a vector of firm-level variables that identify the relevant subsector of the financial institutions based on their SIC code: depository institutions[16] (*Depository*), non-depository credit institutions[17] (*Non_Dep_CI*), broker-dealers and exchange services[18] (*BDES*) and insurance firms[19] (*Insurance*). Each variable takes on the value of 1 if the firm belongs to that particular sub-sector of the financial industry, and zero otherwise. The baseline category is 'holding and other investment offices' which includes firms that have SIC codes starting with 67.

$SurpComp_t$ is the surprise component of the announced policy rate on date *t.* The surprise components of the announced target rates are computed based on Kuttner (2001) approach, which uses data implied by the Fed funds rate futures contracts:

$$SurpComp_t = \frac{D}{D-t}\left(f_{m,t}^0 - f_{m,t-1}^0\right) \tag{22}$$

[16] SIC Code: 60XX

[17] SIC Code: 61XX

[18] SIC Code: 62XX

[19] SIC Code: 63XX and 64XX

where $f_{m,t}^{0}$ is the current-month Fed funds futures rate on day t (the event date) and $f_{m,t-1}^{0}$ is the same rate on the previous day. The variable D is the total number of days in the month. Because the contract's settlement price is based on the monthly average Fed funds rate, the change in the implied futures rate is scaled up by the factor $\frac{D}{D-t}$, which is inversely related to the number of affected days in the month. A table presenting the description of all the variables included in the regressions can be found in Appendix **3**.

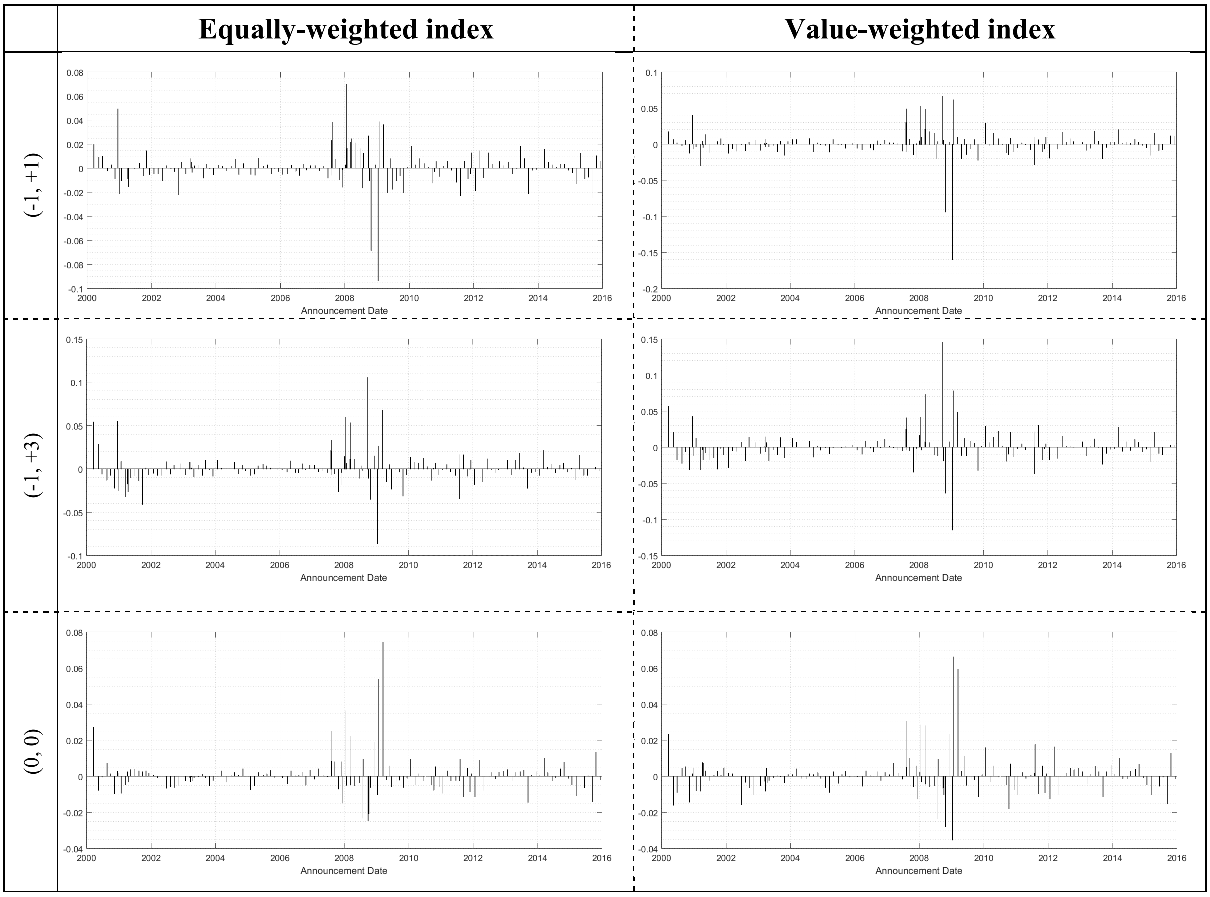
Unlike some previous studies (for example, Ricci (2015)), we focus on the unexpected component of the announced target rates rather than the target rate, as the market predominantly reacts to the unexpected component of the announced rates only (Bernanke and Kuttner 2005; Bredin, Hyde, and Reilly 2010; Chuliá, Martens, and Dijk 2010).

4. Results of the CAR and CMAR estimations

4.1. Descriptive statistics of the estimated CARs and CMARs

Figure 3 and **Figure 4** below show the estimated CARs and CMARs for the 147 monetary policy events over the sample period.The regressions are based on a (-260, -5) estimation window and (-1, +1), (-1, +3) and (0, 0) event windows for the equally-weighted and value-weighted indices of the sample banks. A Market Model is used for estimation of the stock returns and the CRSP value-weighted index is used as the broad market index (consistent with Bernanke and Kuttner (2005)).

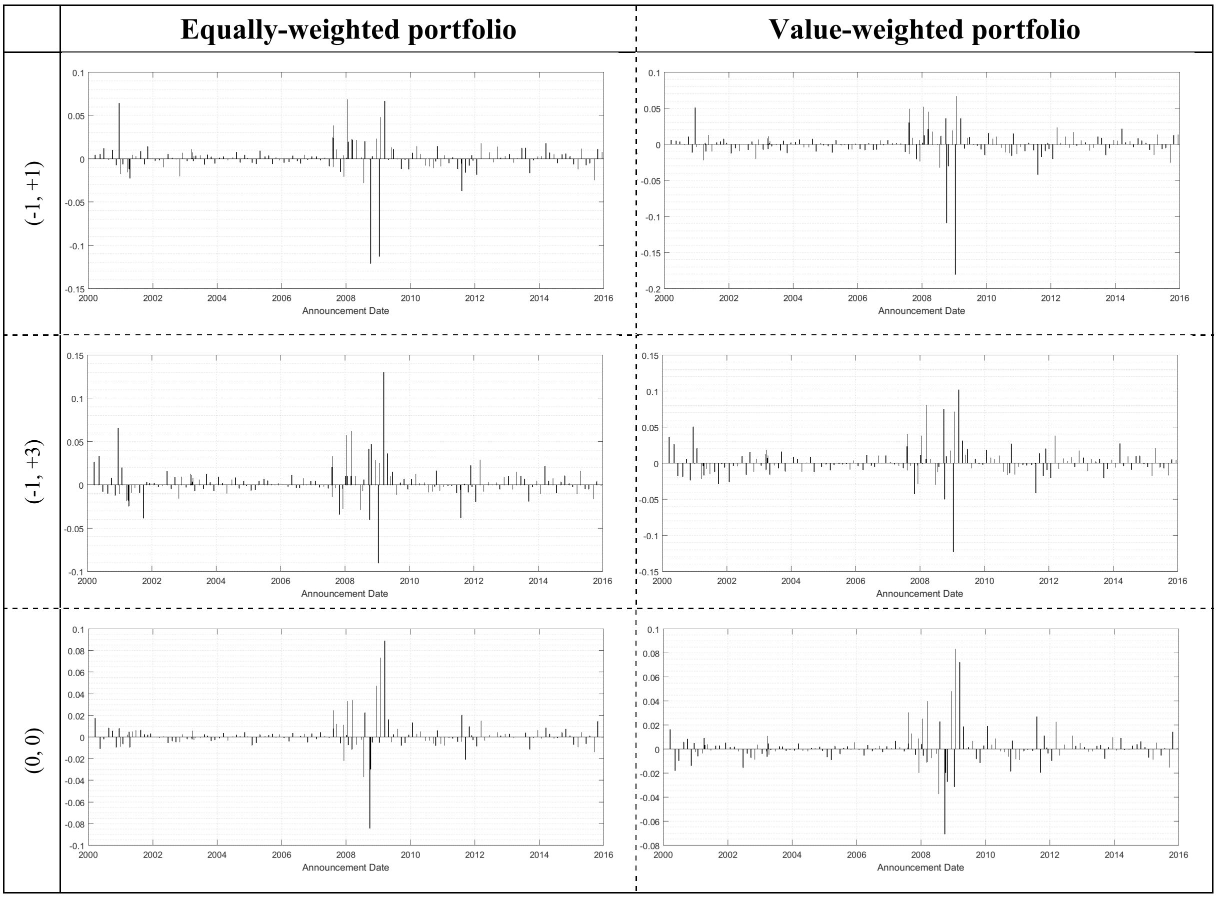
Figure 3 - Estimated CARs on the FOMC announcements dates



Notes: The graphs represent the bar charts of the estimated CARs of the equally-weighted and value-weighted portfolios of the sample firms on the event days over (-1, +1), (-1, +3) and (0, 0) event windows, which are shown in the top, middle and bottom panels respectively. The x axis in each graph represents the event date and the y axis shows the corresponding CAR (in percentage). The estimation window starts on 260 days before the event and ends 5 days prior to the event. The returns are estimated based on a market model with the CRSP value-weighted index as the market proxy. The events are defined as 147 monetary policy announcements by the FOMC that took place during the period from 01/01/2000 to 31/12/2015. The events consider interest rate hikes, interest rate cuts and no-change.

The graphs displayed in **Figure 3** and **Figure 4** suggest that the results for the CAR and CMAR estimations are very similar. There is a significant rise in the abnormal returns during the crisis period. There are also relatively large fluctuations at the early stages of the sample period when the dotcom crash took place. There is a remarkable drop in the levels of both CARs and CMARs after the end of 2008, when the lower bound of the Fed funds rate reached almost zero. However, we can still see some relatively strong reactions to some of the announcements post crisis. This might be a result of the potential surprise component of the announcements. Since the market is likely to expect a rate rise after recovery from the financial crisis, the majority of the announcements in the post-crisis period carry either a negative or zero surprise component.

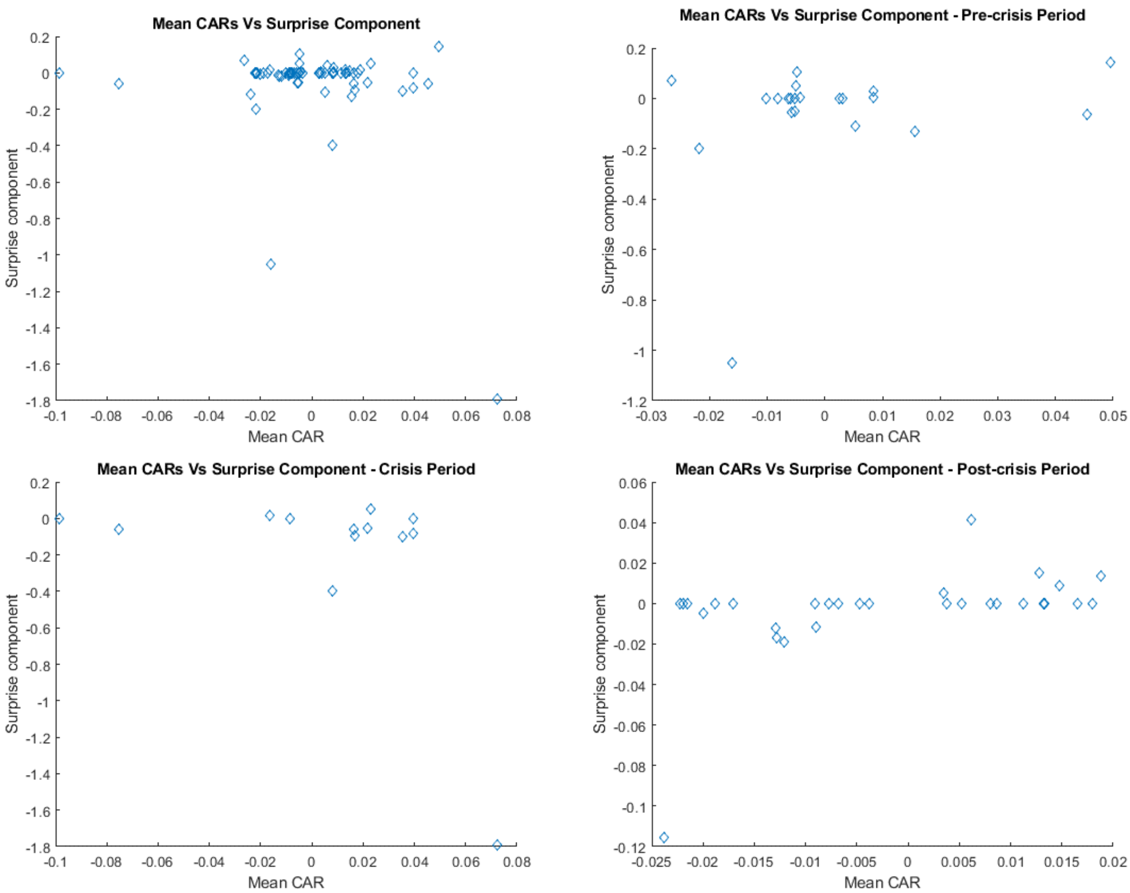
Figure 4 - Estimated CMARs on the FOMC announcements dates



Notes: The bar charts of the estimated CMARs of the equally-weighted and value-weighted portfolios of the sample firms on the event days over (-1, +1), (-1, +3) and (0, 0) event windows which are shown in the top, middle and bottom panels respectively. The x axis in each graph represents the event date and the y axis shows the corresponding CMAR (in percentage). The CRSP value-weighted index is used as the market proxy. The events are defined as 147 monetary policy announcements by the FOMC that took place during the period from 01/01/2000 to 31/12/2015. The events consider interest rate hikes, interest rate cuts and no-change.

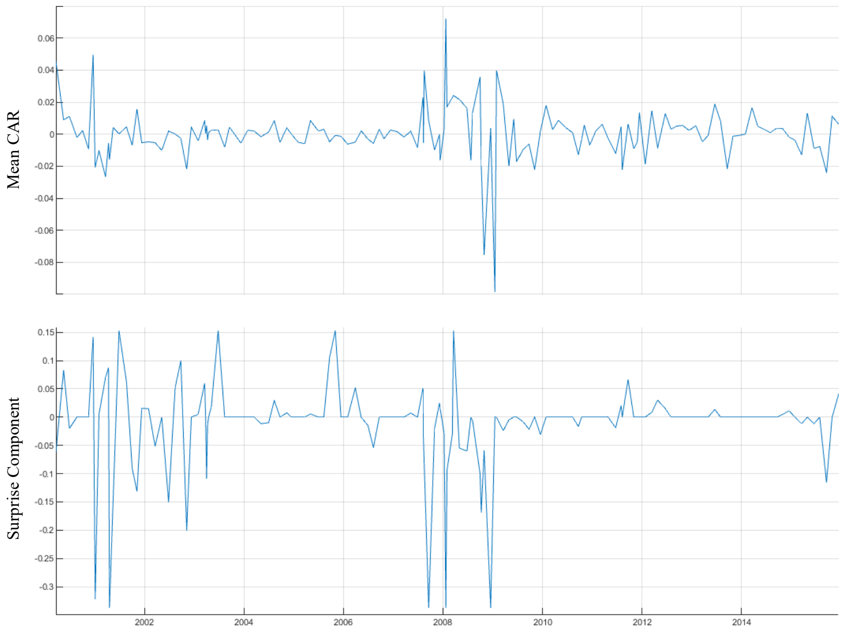
Figure 5 and **Figure 6** illustrate the relation between the surprise components of the target rate announcements and the mean CARs in our sample. Comparing the abnormal returns of the equally-weighted and the value-weighted portfolios we can see a higher volatility and a wider range for the CARs and CMARs of the value-weighted index. This indicates that the larger firms within the sample show a relatively stronger reaction to the monetary policy announcements.

Figure 5 – Plots of mean CAR(-1, +1)s Vs the surprise component of the announced target rates



Notes: The plots demonstrate the relation between the surprise component of each FOMC target rate announcements and the mean CARs generated by our sample firms. The x axis of each graph represents the average CAR of all the sample institutions on each announcement day and the y axis represents the surprise component associated with corresponding announcement. The CARs are estimated over a 3-day event window. The top left plot represents the whole sample period whereas the remaining plots cover the pre-crisis (top right), crisis (bottom left) and post-crisis (bottom left) subsamples. The crisis period is defined as 01/06/2007 until 31/03/2009.

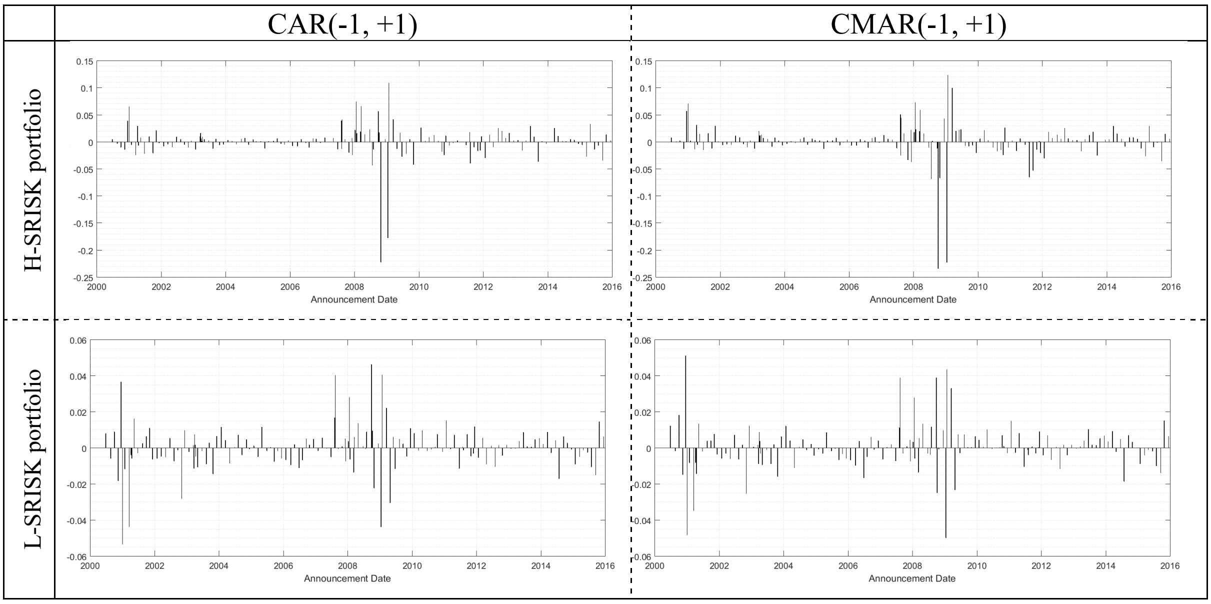
Figure 6 – Comparison between mean CAR(-1, +1)s and the surprise component of the announced target rates



Notes: The top graph represents the mean CAR(-1 , +1) generated by all the sample firms on the FOMC announcement days. The bottom graph shows the surprise component of each corresponding target rate announcement. The x axis represents the sample period, which is common to both graphs. The y axis of the top graph shows the mean of all estimated CARs on the announcement days and the y axis of the bottom graph represents the surprise component of each target rate announcement.

Figure 7 shows the CARs and CMARs for the L-*SRISK* and H-*SRISK* portfolios over the sample period, as well as descriptive statistics for the two portfolios. H-*SRISK* tends to react more strongly to FOMC announcements, especially during the crisis period: The CARs and CMARs for H-*SRISK* are more volatile and their range is wider than for L-*SRISK*.

Figure 7 - Comparison between the reactions of high systemic risk portfolio and low systemic risk portfolio to the monetary policy announcements



	CAR(-1, +1)		*CMAR(-1, +1)*	
	H-SRISK	***L-SRISK***	***H-SRISK***	***L-SRISK***
Mean	0.0390%	0.0160%	0.0680%	0.0445%
Standard Deviation	3.17%	1.28%	3.67%	1.29%
Skewness	-3.1103	-0.2365	-2.9489	0.1364
Kurtosis	25.6082	7.9134	23.1649	8.0404
Minimum	-22.19%	-5.32%	-23.38%	-4.97%
Maximum	10.88%	4.64%	12.35%	5.12%

Notes: The graphs show the estimated CARs (left column) and CMARs (right column) of the H-SRISK (top panel) and L-SRISK (bottom panel) portfolios on the FOMC announcement days over (-1, +1) event windows. The x axes of the graphs represent the announcement dates and the y axes show the magnitude of CARs/CMARS. The H-SRISK portfolio contains the firms that are within the top 20 percentile of the average SRISK distribution every quarter. Similarly, the L-SRISK portfolio contains the firms within the bottom 20 percentile of the average SRISK distribution every quarter. Abnormal returns are estimated using the market model. The proxy for the market portfolio is the CRSP value-weighted index. The table below the graphs show summary statistics for the CARs (left two columns) and CMARs (right two columns) of the H-SRISK and the L-SRISK portfolios.

Table 2 summarises the key information about all the events that have generated a statistically significant mean CAR(-1, +1) at least at 10% level between the 2000-2015 period[20]. In total, 64 of the 147 announcements have generated significant mean CARs according to the calculated ADJ-BMP statistics. The ratio of the statistically significant events to the total number of events in each of the pre-crisis, crisis and post-crisis periods are approximately 32%, 54% and 52% consecutively.

[20] Information about all the events can be found in Appendix **4**.

Table 2 – Key information on the events that generated statistically significant CARs over (-1, +1) event windows

	Date	*No of firms*	*Mean CAR*	*Mean SR*	*Rate change*	*Surprise component*	*Expected component*	*ADJ-BMP*
	Pre-crisis period							
1	21/03/2000	18	0.0455***	0.1235	0.25	-0.0620	0.3120	3.0025
2	19/12/2000	78	0.0496***	0.0518	0	0.1421	-0.1421	5.6822
3	20/03/2001	79	-0.0266***	-0.0301	-0.5	0.0705	-0.5705	-4.4895
4	18/04/2001	79	-0.0160*	-0.0149	-0.5	-1.0500	0.5500	-1.9584
5	06/11/2001	80	0.0156***	0.0301	-0.5	-0.1313	-0.3687	2.7611
6	19/03/2002	81	-0.0053*	-0.0209	0	-0.0517	0.0517	-1.9213
7	07/05/2002	82	-0.0102***	-0.0133	0	0.0000	0.0000	-2.9383
8	06/11/2002	82	-0.0219***	-0.0606	-0.5	-0.2000	-0.3000	-3.9166
9	29/01/2003	82	-0.0042*	-0.0136	0	0.0050	-0.0050	-1.7749
10	01/04/2003	83	0.0053*	0.0097	0	-0.1086	0.1086	1.6817
11	12/08/2003	83	-0.0081***	-0.0512	0	0.0000	0.0000	-3.4197
12	10/08/2004	84	0.0085***	0.0266	0.25	0.0295	0.2205	3.444
13	21/09/2004	86	-0.0051*	-0.0143	0.25	0.0000	0.2500	-1.8049
14	22/03/2005	86	-0.0060***	-0.0249	0.25	0.0000	0.2500	-2.6687
15	03/05/2005	86	0.0084*	0.0237	0.25	0.0055	0.2445	1.9017
16	20/09/2005	86	-0.0048***	-0.0154	0.25	0.1050	0.1450	-2.6132
17	31/01/2006	89	-0.0063***	-0.0919	0.25	0.0000	0.2500	-2.3491
18	28/03/2006	90	-0.0050***	-0.0231	0.25	0.0517	0.1983	-2.6749
19	08/08/2006	91	-0.0058**	-0.0352	0	-0.0539	0.0539	-2.2211
20	20/09/2006	91	0.0031*	0.0164	0	0.0000	0.0000	1.6499
21	12/12/2006	91	0.0026*	0.0561	0	0.0000	0.0000	1.8869
	Crisis period							
22	28/06/2007	92	-0.0084***	-0.0499	0	0.0000	0.0000	-3.4993
23	07/08/2007	91	0.0228***	0.0604	0	0.0517	-0.0517	3.6597
24	16/08/2007	91	0.0395***	0.0725	0	-0.0827	0.0827	5.3901
25	18/09/2007	90	0.0082**	0.0145	-0.5	-0.4000	-0.1000	2.2417
26	11/12/2007	89	-0.0164***	-0.0258	-0.25	0.0155	-0.2655	-2.6119
27	22/01/2008	89	0.0723***	0.1117	-0.75	-1.7911	1.0411	3.4268
28	30/01/2008	89	0.0169*	0.0312	-0.5	-0.0950	-0.4050	1.7618
29	30/04/2008	90	0.0217***	0.0521	-0.25	-0.0550	-0.1950	3.66
30	25/06/2008	89	0.0162***	0.0222	0	-0.0600	0.0600	2.4881
31	29/09/2008	82	0.0355**	0.0154	0	-0.1000	0.1000	2.3084
32	29/10/2008	82	-0.0752***	-0.0234	-0.5	-0.0600	-0.4400	-2.3651
33	16/01/2009	77	-0.0986***	-0.0689	0	0.0000	0.0000	-3.1577
34	28/01/2009	78	0.0397**	0.0257	0	0.0000	0.0000	2.2605
	Post-crisis period							
35	29/04/2009	77	-0.0200*	-0.0271	0	-0.0050	0.0050	-1.6681
36	24/06/2009	77	-0.0171**	-0.0182	0	0.0000	0.0000	-2.231
37	04/11/2009	77	-0.0220***	-0.0488	0	0.0000	0.0000	-2.9626
38	27/01/2010	77	0.0179**	0.0270	0	0.0000	0.0000	2.2971
39	28/04/2010	77	0.0087*	0.0112	0	0.0000	0.0000	1.7134
40	21/09/2010	78	-0.0129***	-0.0393	0	-0.0167	0.0167	-3.6643
41	14/12/2010	77	-0.0068*	-0.0336	0	0.0000	0.0000	-1.7244
42	22/06/2011	77	-0.0121***	-0.0380	0	-0.0187	0.0187	-4.3221
43	09/08/2011	76	-0.0223***	-0.0098	0	0.0000	0.0000	-2.95
44	02/11/2011	76	-0.0091*	-0.0145	0	0.0000	0.0000	-1.8917
45	13/12/2011	76	0.0133***	0.0356	0	0.0000	0.0000	3.2902
46	25/01/2012	76	-0.0189***	-0.1156	0	0.0000	0.0000	-2.8006
47	13/03/2012	76	0.0148***	0.0538	0	0.0086	-0.0086	2.9383
48	20/06/2012	76	0.0128***	0.0298	0	0.0150	-0.0150	3.6995
49	30/01/2013	76	0.0053**	0.0304	0	0.0000	0.0000	2.0194
50	20/03/2013	76	-0.0047*	-0.0143	0	0.0000	0.0000	-1.9002
51	19/06/2013	75	0.0188***	0.0253	0	0.0136	-0.0136	3.7253
52	31/07/2013	75	0.0081***	0.0383	0	0.0000	0.0000	3.0672
53	18/09/2013	75	-0.0216***	-0.0784	0	0.0000	0.0000	-3.5397
54	19/03/2014	74	0.0165***	0.0643	0	0.0000	0.0000	4.9977
55	17/09/2014	72	0.0037**	0.0299	0	0.0000	0.0000	2.2862
56	29/10/2014	74	0.0035*	0.0123	0	0.0050	-0.0050	1.6573
57	28/01/2015	74	-0.0038**	-0.0101	0	0.0000	0.0000	-2.1878
58	18/03/2015	74	-0.0129***	-0.0502	0	-0.0119	0.0119	-6.3686
59	29/04/2015	74	0.0132***	0.0481	0	0.0000	0.0000	4.0262
60	17/06/2015	74	-0.0090***	-0.0397	0	-0.0115	0.0115	-3.6813
61	29/07/2015	74	-0.0077***	-0.0288	0	0.0000	0.0000	-3.6767
62	17/09/2015	74	-0.0238***	-0.0819	0	-0.1154	0.1154	-8.6342
63	28/10/2015	74	0.0112***	0.0393	0	0.0000	0.0000	2.4586
64	16/12/2015	69	0.0061***	0.0149	0.25	0.0413	0.2087	2.8176

*Notes: The table summarises the information about the Fed funds target rate announcements that, based on the ADJ-BMP statistic, generated a significant reaction within the sample financial firms. Mean standardised CARs (Mean SR) and the ADJ-BMP statistic are calculated based on the procedure explained in section 3.2.1. 'Rate change' shows the announced target rate change, which is decomposed into 'Surprise component' and 'Expected component'. Overall 64 out 147 announcements within our sample have generated significant reactions. * $p<0.1$; ** $p<0.05$; *** $p<0.01$*

Table 3 summarises the number of positive and negative reactions to the positive and negative surprises in each of the three periods.

Table 3 – Number of significant positive and negative CARs in each of the sub-periods

	+ Surprises	***- Surprises***
Pre-crisis	3 (+ CARs) / 4 (- CARs)	3 (+ CARs) / 4 (- CARs)
Crisis	1 (+ CARs) / 1 (- CARs)	7 (+ CARs) / 1 (- CARs)
Post-crisis	5 (+ CARs) / 0 (- CARs)	0 (+ CARs) / 6 (- CARs)

Notes: The table presents the number of positive and negative statistically significant average CARs in each of the sub-periods. The signs in parentheses indicate the sign of the average CARs. The columns refer to announcements with positive and negative surprises. As an example, in the pre-crisis period, the positive surprises have generated three statistically significant positive mean CARs and four negative ones.

Unlike the pre-crisis period, the crisis and post-crisis periods each show a relatively clear pattern of how the market evaluates the positive and negative surprises. During the crisis period, we find statistically significant positive CARs for negative surprises in seven out of eight cases. In total (i.e. including the events with non-significant mean CARs) 16 of the 24 Fed funds rate announcements made during the crisis period have been associated with a negative surprise, and only four with a positive surprise (see Appendix **4**). This indicates that during the crisis, the Fed has generally been more dovish than what the market expected. In the post-crisis period however, we see that the financial stocks have benefited from positive surprises and negative surprises generate negative price reaction. A plausible explanation for this result is that in the post-crisis period positive surprises could be perceived as a sign of recovery from the crisis. The results in **Table 3** show that the impact of a changes in interest rates on the financial system changes in the three periods.

Table 4 reports the average CARs and CMARs and the bootstrapped p-values of the equally-weighted and value-weighted portfolios of the sample firms for the different sub-samples and sub-periods over the 147 FOMC announcements about the Fed Funds target rate.

Table 4 - CAR(-1, +1) and CMAR(-1, +1) of the equally-weighted (EW) and value-weighted (VW) portfolios for 147 FOMC announcements.

	Mean CAR(-1, +1)		***Mean CMAR (-1, +1)***		
	EW	***VW***	***EW***	***VW***	***No of events***
Total (entire period)	0.0395%	-0.0032%	0.0785%	-0.0506%	147
+ Surprise	0.3220% (0.1648)	0.3211% (0.1820)	0.4063% (0.2980)	0.3383% (0.3000)	35
- Surprise	0.1193% (0.5314)	0.1349% (0.5060)	0.0862% (0.9800)	-0.0096% (0.9680)	41
Non-Crisis	-0.0594%	-0.0703%	0.0275%	-0.0576%	123
+ Surprise	0.2636% (0.2780)	0.1636% (0.4860)	0.3618% (0.3720)	0.1943% (0.5560)	31
- Surprise	**-0.5239% ** (0.0500)**	-0.3730% (0.1680)	**-0.4693% * (0.0600)**	-0.3923% (0.1800)	25
Crisis	**0.5468% * (0.0580)**	0.3410% (0.2500)	0.3401% (0.3760)	-0.0148% (0.9380)	24
+ Surprise	0.7748% (0.1960)	**1.5422%* (0.0720)**	0.7513% (0.3220)	**1.4547%* (0.0960)**	4
- Surprise	**1.1242% *** (0.0100)**	**0.9284%*** (0.0280)**	**0.9541% * (0.0760)**	0.5884% (0.2100)	16

*Notes: The table summarises the mean CARs and CMARs of the equally-weighted (EW) and value-weighted (VW) portfolios during our entire sample period (top panel), non-crisis period (middle panel) and the crisis period (bottom panel). The crisis period is defined as 01/06/2007 until 31/03/2009 when the global financial crisis took place. Non-crisis period consists of the dates from 01/01/2000 to 31/12/2015 (i.e., our sample period) excluding the crisis period. '- Surprise' and '+ Surprise' refer to announcements associated with negative and positive unexpected target rate changes, respectively. The numbers in parentheses represent the bootstrapped p-values. * p<0.1; ** p<0.05; *** p<0.01*

The sample period is split into crisis and non-crisis periods and the events are divided into announcements with a "Positive Surprise" and announcements with a "Negative Surprise" – the fully anticipated announcements are excluded from these analyses. The numbers in parentheses represent the bootstrapped *p-values*, computed following the procedure described in section **3.2.1**. The results reported in **Table 4** indicate that the financial institutions in our sample do not react significantly to conventional monetary policy news, on average, when the whole sample period is considered.

However, once we divide the sample period into crisis and non-crisis sub-periods, we find some evidence of significant reactions. Unlike the findings from Chuliá, Martens, and Dijk (2010) regarding the aggregate market, our results indicate that for financial institutions negative surprises matter more than positive surprises. This result is inconsistent with those provided by Bernanke and Kuttner (2005), who do not find a strong asymmetry in the effect of the surprise component on the aggregate stock market. Our results however suggest that the price reaction to the negative surprise announcements is state-dependent. While in non-crisis times negative surprises tend to generate negative CARs and CMARs, during the crisis the opposite occurs. These results are similar to those reported by Chen (2007). Our results for the non-crisis period, however, are valid only for the equally-weighted portfolio.

Table 5 presents the results of the same analysis as **Table 4** on the H-*SRISK* and L-*SRISK* portfolios.

Table 5 - CAR(-1, +1) and CMAR(-1, +1) of the H-SRISK and L-SRISK portfolios for 145 FOMC announcements.

	Mean CAR(-1, +1)		***Mean CMAR (-1, +1)***		
	H-SRISK	***L-SRISK***	***H-SRISK***	***L-SRISK***	***No of Events***
Total (entire period)	0.0390%	0.0160%	0.0680%	0.0445%	145
+ Surprises	0.5582% *(-0.1846)*	-0.0148% *(-0.916)*	0.6562% *(-0.2472)*	0.0464% *(-0.952)*	34
- Surprises	0.0338% *(-0.9020)*	0.0782% *(-0.5000)*	-0.0330% *(-0.7600)*	0.0728% *(-0.8120)*	40
Non-Crisis	0.0175%	-0.1038%	0.1695%	-0.0530%	121
+ Surprises	0.3349% *(0.3800)*	-0.0864% *(0.7440)*	0.4247% *(0.5080)*	0.0058% *(0.8780)*	30
- Surprises	-0.2351% *(0.6720)*	**-0.4377%*** ***(0.0560)***	0.0464% *(0.9840)*	**-0.4267%***** ***(0.0280)***	24
Crisis	0.1477%	0.6203%	-0.4437%	0.5362%	24
+ Surprises	**2.2331%*** ***(0.0720)***	0.5225% *(0.2440)*	**2.3924%*** ***(0.0960)***	0.3507% *(0.4780)*	4
- Surprises	0.4370% *(0.3700)*	**0.8522%***** ***(0.0020)***	-0.1522% *(0.7340)*	**0.8221%***** ***(0.0020)***	16

*Notes: The table summarises the mean CARs and CMARs of the H-SRISK and L-SRISK portfolios during our entire sample period (top panel), non-crisis period (middle panel) and the crisis period (bottom panel). The crisis period is defined as 01/06/2007 until 31/03/2009 when the global financial crisis took place. Non-crisis period consists of the dates from 01/01/2000 to 31/12/2015 (i.e., our sample period) excluding the crisis period. '- Surprise' and '+ Surprise' refer to announcements associated with negative and positive unexpected target rate changes, respectively. The numbers in parentheses represent the bootstrapped p-values. * p<0.1; ** p<0.05; *** p<0.01*

Because these portfolios are rebalanced quarterly, the sample period starts from the second quarter of 2000 in this case, and the total number of the announcements drop to 145. The results exhibit a similar behaviour of the L-*SRISK* portfolio to the equally-weighted aggregate portfolio. Both the L-*SRISK* and the equally-weighted portfolios react mainly to negative surprises. The H-*SRISK* - portfolio, however, exhibits a significantly positive reaction to positive surprises during the crisis. This is consistent with the "TBTF hypothesis": investors rebalance their portfolios toward the TBTF institutions in correspondence of positive surprises.

4.2. Regression analyses of the estimated CARs and CMARs

4.2.1. Portfolio time series approach

In the first stage of the regression analysis we adopt the portfolio time-series approach similar to Berkman, Cole, and Fu (2010). For this purpose, we build a portfolio named 'High minus low *SRISK*' that is long in the H-*SRISK* portfolio and short in the L-*SRISK* portfolio (as described in the previous section). We regress the daily returns of this portfolio on the market return and two dummy variables that control for FOMC rate announcements with positive and negative surprises. The results of this regression can show us whether systemically risky institutions show a significant reaction to the monetary policy news while controlling for the market return. In order to investigate whether this reaction is associated with the systemic risk of the institutions, we run the same regression as above for the equally-weighted and value-weighted aggregate portfolios of the firms. The comparison between the results of the three regressions provides evidence of the possible role of systemic risk in how the firms react to the monetary policy news.

Table 6 summarises the results from regressions of the daily returns of the "High minus low *SRISK*" portfolio and the aggregate portfolios on the market return and the two dummies for the monetary policy announcements from 01/01/2000 to 31/12/2015. The market index used is the CRSP value-weighted index, denoted by *CRSPVW*. The numbers in parentheses represent the *t-statistics* calculated using Newey-West standard errors.

The results in **Table 6** suggest that FOMC announcements with a positive surprise component have a significantly positive impact on the stock returns of the institutions with high systemic risk. In particular, the return on the "High minus low *SRISK*" portfolio is 0.55% higher on announcement dates related to positive surprises. This effect however is not observed for the other two portfolios.

Table 6 - Results from time-series regressions

	High minus low SRISK portfolio	***Equally-weighted portfolio***	***Value-weighted portfolio***
CRSPVW	0.6439***	1.2951***	1.3044***
	(9.1185)	(26.6005)	(26.6519)
Positive_Surp	**0.0055****	**0.0008**	**0.0008**
	(2.0061)	**(0.6381)**	**(0.5622)**
Negative_Surp	**-0.0009**	**-0.0004**	**-0.0004**
	(-0.2315)	**(-0.1258)**	**(-0.1400)**
_cons	-0.0001	0.0003*	0.0000
	(-0.5049)	(1.8816)	(-0.1602)

Notes: The table presents the results from regression analysis of our sample portfolios. The first column represents a portfolio that is long in the H-SRISK portfolio and short in the L-SRISK portfolio. The estimated model is:

$$R(HighSRISK_t) - R(LowSRISK_t) = \alpha + \beta_1 CRSPVW_t + \beta_2 PositiveSurp_t + \beta_3 NegativeSurp_t + \varepsilon_t$$

*In the second and third columns the left side of the equation is substituted with the daily returns of the equally-weighted (EW) and value-weighted (VW) portfolios of the sample firms respectively. The dummy variable Positive_Surp is equal to 1 on the days of FOMC Fed funds target rate announcements with higher-than-expected rates announced and zero otherwise. The variable Negative_Surp is equal to 1 on the days of lower-than-expected rate announcements and zero otherwise. CRSPVW denotes the market index. The numbers in parentheses represent the Newey-West t-statistics of the estimated coefficients. * p<0.1; ** p<0.05; *** p<0.01.*

4.2.2. Panel data approach

Table 7 summarises the results from panel data regressions analysing the determinants of the estimated 3-day CARs. All the variables in all the regressions (including the CARs) are winsorized at 1% and 99% levels. The first three columns report results of regressions of the CARs on *SRISK*, without any control variables, splitting the sample into announcements with negative, positive and zero surprise elements. The next three columns report results including control variables. The last two columns analyse the entire sample covering all the events, controlling for *SurpComp*. The difference between the 7th and the 8th column is that in the former *SurpComp* is included with the outliers while in the latter *SurpComp* is winsorized at 1% and 99% level. We cluster the standard errors at the firm level. The numbers in parentheses are the Z statistics of the coefficients.

Table 7 - Results for CAR panel data regressions: 3-day event window

CAR(-1, +1)	***Negative Surprise***	***Positive Surprise***	***Zero Surprise***	***Negative Surprise***	***Positive Surprise***	***Zero Surprise***	***Whole sample***	***Whole sample***
SRISK	**-0.00006**	**0.00011**	**-0.00006**	**-0.00010**	**0.00008**	**-0.00005**	**-0.00004**	**-0.00004**
	(1.76)*	(4.41)***	(4.74)***	(2.58)***	(3.12)***	(3.68)***	(2.65)***	(2.68)***
Market_Cap				0.00053	-0.00018	0.00005	0.00006	0.00006
				(0.90)	(0.45)	(0.21)	(0.24)	(0.25)
MtB				-0.00061	-0.00045	0.00003	-0.00030	-0.00030
				(1.81)*	(1.40)	(0.15)	(1.94)*	(1.94)*
SurpComp							-0.00666	-0.00372
							(3.02)***	(1.56)
Rate_Hike				0.00665	-0.04218	-0.00366	0.00176	0.00170
				(2.94)***	(5.69)***	(2.70)***	(1.59)	(1.52)
Rate_Cut				-0.01035	-0.00754		-0.00529	-0.00481
				(4.62)***	(3.42)***		(3.95)***	(3.61)***
Subprime				-0.00382	0.00243	-0.00820	0.00518	0.00517
				(0.83)	(0.96)	(3.85)***	(3.27)***	(3.26)***
Global				-0.02656		0.00665	-0.01596	-0.01644
				(4.19)***		(1.22)	(3.09)***	(3.21)***
Postcrisis				-0.04342	-0.00245	0.00646	-0.02081	-0.02128
				(4.04)***	(0.44)	(2.42)**	(2.84)***	(2.93)***
Depository				-0.00002	-0.00164	-0.00130	-0.00099	-0.00099
				(0.00)	(0.89)	(1.73)*	(0.91)	(0.91)
Non_Dep_CI				-0.00070	-0.00249	-0.00060	-0.00099	-0.00099
				(0.18)	(1.22)	(0.53)	(0.88)	(0.88)
BDES				-0.00032	0.00334	-0.00130	0.00020	0.00020
				(0.08)	(1.49)	(1.27)	(0.17)	(0.18)
Insurance				-0.00468	-0.00250	0.00052	-0.00160	-0.00160
				(1.24)	(1.36)	(0.61)	(1.53)	(1.53)
_cons	0.01843	0.03133	-0.00317	0.01565	0.05444	-0.00345	0.01234	0.01224
	(4.75)***	(9.16)***	(1.46)	(1.87)*	(9.24)***	(1.02)	(4.06)***	(4.03)***
N	*3,307*	*2,828*	*5,664*	*3,305*	*2,822*	*5,652*	*11,779*	*11,779*
R^2	*0.0402*	*0.0874*	*0.0199*	*0.0721*	*0.1181*	*0.0221*	*0.0320*	*0.0308*

*Notes: The table presents the results from panel data regressions of the estimated CARs. The CARs are estimated using (-260, -5) estimation windows and (-1, +1) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

The coefficients of *SRISK* are highly significant in almost all the specifications in **Table 7**. The sign of *SRISK* coefficient and the sign of the surprise component are consistent throughout, suggesting that more systemically risky financial institutions generally exhibit a more positive (negative) response to positive (negative) surprises. These results corroborate the earlier evidence reported in Tables **4** to **6**. Overall our findings support the view that the TBTF institutions, which are found to be less exposed to tail risk (Gandhi and Lustig 2015), show a better performance whenever the rates are unexpectedly high. We argue that this is because an unexpected increase in the short-term interest rates is associated with higher distress risk for the financial system and the economy (Ang, Piazzesi, and Wei 2006). The negative coefficient of *SurpComp* in **Table 7** also confirms this view and is consistent with the "TBTF hypothesis".

Nevertheless, the negative coefficient of SRISK for the whole sample regressions in columns seven and eight of **Table 7** suggests that riskier financial institutions tend to have lower abnormal returns on the FOMC announcement days. Previous contributions also suggest that different types of risk negatively affect bank abnormal returns (Bruno, Onali, and Schaeck 2018). However, our results in columns two and five show that for positive surprises systemic risk increases abnormal returns. This demonstrates the unique nature of systemic risk: although conventionally it is considered as a form of risk, in some cases investing in institutions with high systemic risk might be safe, because of TBTF considerations. This can potentially give financial institutions the incentive to deliberately inflate their level of systemic risk, especially at times of crisis. This is the key result of our paper.

Similar results are presented in **Table A.5** to **Table A.9** (in Appendix **5**) to for CARs estimated using a 1-day and 5-day event windows and for CMARs estimated using 1-, 3- and 5-day event windows. As an additional robustness test, we also run the same regressions as in **Table 7** on CARs estimated using a 4-factor Fama-French-Carhart model. The results, reported in **Table A.11**, suggest that changing the estimation model for the abnormal returns does not alter our results substantially. In particular, for events related to positive surprises, the coefficient of *SRISK* remains constantly significant and positive in all the cases. Importantly, in the regressions for events related to negative or zero surprises the coefficient of SRISK is either insignificant or negative and significant (**Table 7**, **Table A.6**, **Table A.7** and **Table A.9**).[21] These results are consistent with the "TBTF hypothesis".

We also provide some evidence of a negative impact of the surprise component on the CARs and CMARs for the regressions including *SurpComp* (i.e. the "whole sample" regressions). This effect is more pronounced in the case for the 1-day event window. The negative coefficient of *SurpComp* is consistent with the findings of Altavilla, Boucinha, and Peydró (2018) and English, Van den Heuvel, and Zakrajšek (2018). This finding suggests that the financial sector reacts to the interest rate decisions in a similar manner to the aggregate market (Bernanke and Kuttner 2005). Based on the estimated coefficient in the case for 1-day event window, a hypothetical increase in the surprise component equal to 25 basis points reduces the average CAR by about 16 basis points.

Our results also show an asymmetric response of financial stocks to interest rate hikes and cuts, when we consider negative and positive surprises. The coefficient of *Rate_Hike* is positive and (in most cases) statistically significant for the specifications related to negative surprises, but it tends to be negative and statistically significant for the specifications related to positive surprises. On the other hand, *Rate_Cut* tends to have a negative and statistically significant coefficient both for negative and for positive surprises.

Finally, we do not find evidence that there is a significant difference between the responses of different subsectors to the FOMC announcements.

4.2.3. The role of the yield curve

As previously discussed, the yield curve can play an important role in our analysis for two reasons. First, the slope of the yield curve might convey signals to the market about an impending recession.[22]

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[21] There is no rate cut announcements included within the "Zero Surprise" subsample and the subsample only covers rate hike and constant rate announcements.

[22] Almost all the NBER recession periods since 1964 have been preceded by an inverted yield curve.

If this is true, a change in the slope of the yield curve may affect the market reaction to changes in the target rate.[23] Second, Borio, Gambacorta, and Hofmann (2017) find that a steeper yield curve is beneficial for bank profitability. With a flatter yield curve, the profits of the financial institutions that engage in maturity transformation are likely to be squeezed. Therefore, the shape of the yield curve might affect market expectations and the price reaction to FOMC announcements because of the potential impact on bank profits.

To investigate how the yield curve can influence the reaction of the financial institutions to monetary policy changes we run regressions based on equations (20) and (21) on the whole sample of FOMC announcements (i.e., regardless of whether there are positive, negative or zero surprises), after including the variable *Term_Spread* (the difference between the yields of 10-year Treasury Bonds and 3-month Treasury Bills) as an explanatory variable. We also introduce three variables: a dummy variable equal to one if the term spread is below its sample mean, *flat_yc*; the interaction between this dummy and *SRISK*, *SRISK_flat_yc*; and the interaction between this dummy and the surprise component, *SurpComp_flat_yc*. The inclusion of these variables enables us to understand the role of a flattening yield curve in the price reaction. In addition, we interact systemic risk with positive surprises, *SRISK_PS*, to validate our previous findings regarding the role of systemic risk, using a different approach (i.e., using an interaction term instead of sample splits).

Table 8 reports the results from these regressions. Similar to our previous findings, there is a negative relation between systemic risk and the abnormal returns in general. However, systemic risk tends to increase the abnormal returns whenever the announcement carries a positive surprise component or whenever the yield curve is relatively flat, as suggested by the positive coefficients of

[23] Several studies so far have documented the strong predictive power of the yield curve when forecasting upcoming recessions (among others: Estrella 2005; Ang, Piazzesi, and Wei 2006; Rudebusch and Williams 2009). **Figure 1** provides us with an overview of the relation between the short-term rates, the slope of the yield curve and recessions since 1985.

SRISK_PS and *SRISK_flat_yc*. These findings are consistent with our TBTF hypothesis, because both positive surprises and a reduction in the term spread can signal that a financial crisis might be imminent.

Table 8 - The role of the yield curve

	(1)	*(2)*	*(3)*	*(4)*
	CAR(1, 1)	***CAR(1, 1)***	***CMAR(1, 1)***	***CMAR(1, 1)***
SRISK	**-0.00009**	**-0.00009**	**-0.00007**	**-0.00007**
	(4.16)***	(4.15)***	(2.94)***	(2.92)***
SRISK_flat_yc	**0.00007**	**0.00007**	**0.00007**	**0.00007**
	(2.10)**	(2.19)**	(2.02)**	(2.08)**
SRISK_PS	**0.00016**	**0.00015**	**0.00010**	**0.00009**
	(4.67)***	(4.65)***	(2.80)***	(2.77)***
SurpComp	-0.00390	0.01039	-0.00139	0.00910
	(1.66)*	(2.66)***	(0.51)	(2.28)**
SurpComp_flat_yc		-0.01943		-0.01423
		(3.24)***		(2.24)**
Term_Spread	0.00151	0.00188	0.00069	0.00096
	(1.72)*	(2.14)**	(0.81)	(1.15)
Flat_yc	0.00078	0.00067	-0.00110	-0.00116
	(0.58)	(0.50)	(0.78)	(0.81)
Market_Cap	0.00014	0.00013	-0.00017	-0.00017
	(0.57)	(0.53)	(0.58)	(0.60)
MtB	-0.00026	-0.00027	0.00014	0.00014
	(1.73)*	(1.74)*	(0.92)	(0.91)
Rate_Hike	0.00183	0.00172	-0.00053	-0.00063
	(1.63)	(1.53)	(0.45)	(0.55)
Rate_Cut	-0.00514	-0.00722	-0.00167	-0.00319
	(3.85)***	(4.63)***	(1.22)	(1.95)*
Subprime	0.00370	0.00385	0.00274	0.00285
	(2.14)**	(2.22)**	(1.61)	(1.67)*
Global	-0.01864	-0.01463	-0.02024	-0.01729
	(3.58)***	(2.62)***	(4.09)***	(3.24)***
Postcrisis	-0.02520	-0.02156	-0.02422	-0.02153
	(3.30)***	(2.72)***	(3.50)***	(2.96)***
Depository	-0.00092	-0.00091	-0.00109	-0.00108
	(0.86)	(0.85)	(0.96)	(0.96)
Non_Dep_CI	-0.00116	-0.00116	-0.00196	-0.00196
	(1.01)	(1.02)	(1.48)	(1.48)
BDES	0.00000	0.00000	0.00150	0.00150
	(0.00)	(0.00)	(1.23)	(1.22)
Insurance	-0.00156	-0.00155	-0.00095	-0.00095
	(1.51)	(1.50)	(0.90)	(0.90)
_cons	0.01136	0.01185	0.01699	0.01732
	(3.86)***	(4.04)***	(3.41)***	(3.49)***
N	11,779	11,779	12,004	12,004

*Notes: The table presents the panel data regression results of the estimated CARs and CMARs. The regressions test for the effect of yield curve data on the 3-day CARs and CMARs and potential non-linearities in the impact of SRISK on the CARs and CMARs. Term_Spread is the difference between 10-year and 3-month treasury bill yields. We assume the yield curve is "flattening" whenever the term spread is below its sample mean. SRISK_flat_yc is the interaction term between SRISK and a flattening yield curve. SRISK_PS is the interaction term between SRISK and positive surprises. Lastly, SurpComp_flat_yc is the interaction term between the surprise component and a flattening yield curve. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01*

The results from **Table 8** also suggest that the term spread positively affects the CARs and CMARs. This suggests that the financial institutions tend to profit from "riding the yield curve". A similar positive impact of the yield curve on banking profitability has been documented in other studies (Borio, Gambacorta, and Hofmann 2017). The surprise component generally tends to reduce the abnormal returns, consistent with our previous findings and the evidence provided by English, Van den Heuvel, and Zakrajšek (2018) and Altavilla, Boucinha, and Peydró (2018).

In columns 2 and 4 of **Table 8** we include an additional variable, *SurpComp_flat_yc*, which is the interaction between the surprise component, *SurpComp*, and the dummy *flat_yc.* This analysis aims to understand whether the impact of *SurpComp* changes when the yield curve changes shape. The coefficients of *SRISK*, *SRISK_PS* and *SRISK_flat_yc* remain significant and with the same sign as in columns 1 and 3 of **Table 8**, so our main results about *SRISK* and the role of positive surprises and a flatter yield curve remain valid.[24]

However, the coefficients of *SurpComp* are positive and significant, suggesting that financial institutions react well, on average, to higher-than-expected changes in target rates. The coefficients of *SurpComp_flat_yc* are negative and significant, and the magnitude of the coefficients is larger than the coefficients of *SurpComp*. These results suggest that the effect of *SurpComp* on the price reaction changes according to the shape of the yield curve. Since the shape of the yield curve can signal that a crisis is imminent, in the next section we examine crisis and non-crisis periods separately.

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[24] We also examine the impact of very low interest rates on the price reaction. In untabulated results (available upon request), we interact the variable *SurpComp* with a dummy equal to one if interest rates are between 0 basis points and 25 basis points (*SurpZLB).* We also control for the other variables as in **Table 8**. The coefficient of *SurpZLB* is positive and statistically significant, suggesting that when interest rates are very low higher than expected target rates have a positive impact on the CARs and CMARs. This is consistent with the view that positive surprises benefit banks when interest rates are close to zero, because banks are reluctant to pass negative interest rates on to depositors (Heider, Saidi, and Schepens 2019).

4.2.4. Systemic risk and the crisis period

The financial crisis of 2007-2009 was a result of systemic failures within the global financial system. During a financial crisis, the stock market movements of systemically important institutions is of particular importance because of the broad impact they can have on the aggregate market. Therefore, monetary policy interventions occurring during crises are expected to have a positive impact on the institutions with high systemic risk.

Table 9 and **Table 10** present the results of the panel data regressions of the CARs and CMARs where systemic risk is interacted with the crisis period.

Table 9 - Systemic risk and the crisis period – CAR(-1, +1)

CAR(-1, +1)	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*
SRISK	**-0.00013**	**0.00004**	**-0.00003**
	(3.80)***	(1.47)	(2.14)**
SRISK_Crisis	**0.00006**	**0.00018**	**-0.00026**
	(0.73)	(1.87)*	(2.36)**
Market_Cap	0.00047	-0.00026	0.00009
	(0.78)	(0.66)	(0.36)
MtB	-0.00061	-0.00044	0.00004
	(1.82)*	(1.34)	(0.16)
Rate_Hike	0.00663	-0.04220	-0.00367
	(2.93)***	(5.69)***	(2.71)***
Rate_Cut	-0.01033	-0.00765	
	(4.62)***	(3.46)***	
Subprime	0.00999	0.00220	-0.00894
	(0.92)	(0.87)	(4.13)***
Global	-0.01282		
	(1.48)		
Postcrisis	-0.02917	-0.00220	-0.00227
	(6.63)***	(0.40)	(0.44)
Depository	0.00003	-0.00158	-0.00132
	(0.01)	(0.86)	(1.77)*
Non_Dep_CI	-0.00071	-0.00256	-0.00059
	(0.18)	(1.26)	(0.52)
BDES	-0.00028	0.00337	-0.00134
	(0.07)	(1.51)	(1.31)
Insurance	-0.00463	-0.00242	0.00049
	(1.23)	(1.32)	(0.58)
_cons	0.01595	0.05495	-0.00371
	(1.87)*	(9.30)***	(1.10)
N	3,305	2,822	5,652
R^2	0.0722	0.1194	0.0240

*Notes: The table reports the results from the panel data regressions of the estimated CARs on SRISK and an interaction term between SRISK and the crisis period as well as other control variables. The CARs are estimated over (-260, -5) estimation windows and (-1, +1) event windows. The column labelled 'Positive surprise' ('Negative surprise') refers to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. All estimations are done using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01*

Table 10 – Systemic risk and the crisis period – CMAR(-1, +1)

CMAR(-1, +1)	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*
SRISK	**-0.00009**	**0.00001**	**-0.00002**
	(1.86)*	(0.24)	(1.01)
SRISK_Crisis	**0.00004**	**0.00025**	**-0.00034**
	(0.51)	(2.38)**	(2.93)***
Market_Cap	-0.00023	-0.00026	-0.00008
	(0.33)	(0.64)	(0.32)
MtB	-0.00033	0.00011	0.00046
	(0.98)	(0.35)	(2.32)**
Rate_Hike	0.00103	-0.06039	-0.00273
	(0.47)	(7.45)***	(2.06)**
Rate_Cut	-0.00579	-0.00647	
	(2.42)**	(2.18)**	
Subprime	0.04453	0.00316	-0.00981
	(4.41)***	(1.11)	(4.80)***
Global	0.01925		
	(2.37)**		
Postcrisis	-0.01989	0.00529	0.01624
	(5.52)***	(0.95)	(3.02)***
Depository	-0.00025	-0.00120	-0.00162
	(0.08)	(0.67)	(1.91)*
Non_Dep_CI	-0.00262	-0.00268	-0.00117
	(0.74)	(1.13)	(1.03)
BDES	0.00294	0.00450	-0.00075
	(0.86)	(2.16)**	(0.70)
Insurance	-0.00375	-0.00166	0.00099
	(1.19)	(0.94)	(1.06)
_cons	0.01407	0.06756	0.00078
	(1.13)	(8.99)***	(0.15)
N	3,412	2,863	5,729
R^2	0.0647	0.1354	0.0311

Notes: The table reports the results from the panel data regressions of the estimated CMARs on SRISK and an interaction term between SRISK and the crisis period as well as other control variables. The CMARs are estimated over (-1, +1) event windows. The column labelled 'Positive surprise' ('Negative surprise') refers to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. All estimations are done using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * *p<0.1;* ** *p<0.05;* *** *p<0.01*

The crisis period in this case is defined as the sum of the 'subprime' and 'global' phases of the crisis. The purpose of these tests is to investigate whether the institutions with high systemic risk react to monetary policy announcements during the crisis period in a different fashion relative to the rest of the sample period.

In these tables, the variable *SRISK_Crisis* is the interaction term between the crisis period and *SRISK*. The coefficients of *SRISK* and *SRISK_Crisis* are jointly significant at 5% level only in the case for zero surprises. The subsample of events with a 'Zero Surprise' includes only rate hike and unchanged rate announcements over the whole sample period, but no rate hikes took place during the crisis period. Therefore, these results indicate that financial institutions with high systemic risk showed a worse response to fully anticipated unchanged rate announcements during the crisis period. Such policy announcements during crisis can be seen by the investors as an indication of central bank's lack of willingness to interfere in the crisis. Therefore, consistent with the findings of (Correa et al. 2014) the TBTF institutions are hit more severely in such situations. Fiordelisi and Ricci (2016) also find negative reactions in bank stock returns and CDS spreads to instances where public authorities decide not to intervene in an ongoing crisis - allowing bank failures (inactions) or bailouts (late actions).

4.2.5. Systemic Risk Vs the G-SIFI label

Our results so far suggest that the investors tend to consider high systemic risk as a sign of a safer investment when the interest rates rise. An important reason behind this interpretation of systemic risk could be the TBTF label entitled to some financial institutions. To investigate whether it is the quantitative level of systemic risk or the TBTF label that matter the most, we run our regressions including a *G-SIFI* variable. For this purpose, we create a dummy variable, that controls for the Global Systemically Important Financial Institutions (G-SIFIs) introduced by the Financial Stability Board (FSB) every year since 2011. According to the FSB's evaluation, the G-SIFI's are the financial institutions whose failure would cause significant distress to the system, hence additional policy measures are required to contain the risk of these institutions.

Table 11 and **Table 12** present the results of our regressions with the G-SIFI variable. We run the same models as in **Table 7** and **Table 8** only adding *G-SIFI* to the explanatory variables. The results show that, although both *G-SIFI* and *SRISK* tend to have similar effects, the effect of *SRISK* is much stronger in terms of statistical significance. This indicates that the market identifies the TBTF institutions predominantly based on their present systemic risk levels rather than the labels given to them by the authorities. Nevertheless, in case for the negative surprises, as presented in **Table 11**, we observe a significant negative impact of the *G-SIFI* label, similar to that of *SRISK.* This, as explained earlier, suggests that the investors rebalance their portfolios towards financial institutions with less systemic risk (and consequently without public implicit guarantees), when the interest rates are reduced.

Table 11 - The effect of the G-SIFI label

CAR(-1, +1)	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**-0.00006**	**0.00011**	**-0.00006**	**-0.00009**	**0.00008**	**-0.00005**	**-0.00004**	**-0.00004**
	(1.57)	(3.72)***	(3.71)***	(2.38)**	(2.61)***	(3.14)***	(2.42)**	(2.38)**
G-SIFI	**-0.00485**	**-0.00043**	**0.00021**	**-0.00627**	**0.00078**	**0.00043**	**-0.00031**	**-0.00033**
	(1.85)*	(0.14)	(0.16)	(2.20)**	(0.21)	(0.29)	(0.23)	(0.24)
Market_Cap				0.00060	-0.00020	0.00003	0.00007	0.00007
				(1.01)	(0.49)	(0.11)	(0.27)	(0.26)
MtB				-0.00061	-0.00045	0.00003	-0.00030	-0.00030
				(1.82)*	(1.39)	(0.15)	(1.94)*	(1.94)*
SurpComp							-0.00372	-0.00666
							(1.56)	(3.02)***
Rate_Hike				0.00665	-0.04218	-0.00366	0.00170	0.00176
				(2.94)***	(5.69)***	(2.70)***	(1.52)	(1.59)
Rate_Cut				-0.01035	-0.00753		-0.00481	-0.00529
				(4.62)***	(3.42)***		(3.61)***	(3.95)***
Subprime				0.01066	0.00244	-0.00820	0.00517	0.00517
				(0.99)	(0.96)	(3.85)***	(3.26)***	(3.27)***
Global				-0.01206			-0.01644	-0.01596
				(1.39)			(3.21)***	(3.09)***
Postcrisis				-0.02893	-0.00255	-0.00019	-0.02128	-0.02081
				(6.49)***	(0.46)	(0.04)	(2.93)***	(2.84)***
Depository				0.00002	-0.00165	-0.00131	-0.00098	-0.00098
				(0.00)	(0.90)	(1.75)*	(0.90)	(0.90)
Non_Dep_CI				-0.00075	-0.00246	-0.00059	-0.00100	-0.00100
				(0.19)	(1.21)	(0.51)	(0.89)	(0.89)
BDES				-0.00031	0.00335	-0.00131	0.00020	0.00020
				(0.08)	(1.49)	(1.27)	(0.18)	(0.17)
Insurance				-0.00467	-0.00250	0.00052	-0.00160	-0.00160
				(1.25)	(1.37)	(0.61)	(1.53)	(1.53)
_cons	0.01845	0.03133	-0.00317	0.01497	0.05467	-0.00326	0.01215	0.01224
	(4.76)***	(9.12)***	(1.47)	(1.78)*	(9.31)***	(0.90)	(3.87)***	(3.91)***
N	3,307	2,828	5,664	3,305	2,822	5,652	11,779	11,779

Notes: The table presents the results from panel data regressions of the estimated CARs. The CARs are estimated using (-260, -5) estimation windows and (-1, +1) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. G-SIFI is a dummy variable indicating the institutions that are labelled as G-SIFIs by the FSB. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels like all other variables in all cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. p<0.1; ** p<0.05; *** p<0.01.*

Table 12 - The effect of the G-SIFI label without sample splits

	(1)	(2)	(3)	(4)
	CAR(1, 1)	***CAR(1, 1)***	***CMAR(1, 1)***	***CMAR(1, 1)***
SRISK	**-0.00009**	**-0.00009**	**-0.00007**	**-0.00007**
	(3.93)***	(3.92)***	(2.82)***	(2.80)***
G-SIFI	**-0.00059**	**-0.00058**	**-0.00024**	**-0.00024**
	(0.46)	(0.45)	(0.16)	(0.16)
SRISK_flat_yc	**0.00007**	**0.00007**	**0.00007**	**0.00007**
	(2.10)**	(2.19)**	(2.02)**	(2.08)**
SRISK_PS	**0.00016**	**0.00016**	**0.00010**	**0.00009**
	(4.69)***	(4.66)***	(2.77)***	(2.74)***
SurpComp	-0.00391	0.01038	-0.00139	0.00910
	(1.66)*	(2.66)***	(0.51)	(2.28)**
SurpComp_flat_yc		-0.01943		-0.01423
		(3.24)***		(2.24)**
Term_Spread	0.00151	0.00188	0.00069	0.00096
	(1.72)*	(2.14)**	(0.81)	(1.15)
Flat_yc	0.00078	0.00067	-0.00110	-0.00116
	(0.59)	(0.50)	(0.78)	(0.81)
Market_Cap	0.00016	0.00015	-0.00016	-0.00016
	(0.60)	(0.56)	(0.50)	(0.53)
MtB	-0.00026	-0.00027	0.00014	0.00014
	(1.73)*	(1.74)*	(0.92)	(0.91)
Rate_Hike	0.00183	0.00172	-0.00052	-0.00063
	(1.63)	(1.53)	(0.45)	(0.54)
Rate_Cut	-0.00514	-0.00722	-0.00167	-0.00319
	(3.85)***	(4.63)***	(1.22)	(1.95)*
Subprime	0.00370	0.00385	0.00273	0.00285
	(2.14)**	(2.22)**	(1.61)	(1.67)*
Global	-0.01863	-0.01463	-0.02024	-0.01729
	(3.58)***	(2.62)***	(4.09)***	(3.24)***
Postcrisis	-0.02520	-0.02156	-0.02422	-0.02153
	(3.30)***	(2.72)***	(3.50)***	(2.96)***
Depository	-0.00091	-0.00090	-0.00108	-0.00108
	(0.85)	(0.84)	(0.96)	(0.95)
Non_Dep_CI	-0.00118	-0.00118	-0.00197	-0.00197
	(1.03)	(1.03)	(1.49)	(1.49)
BDES	0.00000	0.00000	0.00150	0.00150
	(0.00)	(0.00)	(1.23)	(1.22)
Insurance	-0.00155	-0.00155	-0.00095	-0.00095
	(1.51)	(1.51)	(0.90)	(0.90)
_cons	0.01117	0.01168	0.01686	0.01719
	(3.68)***	(3.85)***	(3.16)***	(3.24)***
N	11,779	11,779	12,004	12,004

*Notes: The table presents the panel data regression results of the estimated CARs and CMARs. The regressions test for the effect of yield curve data and the G-SIFI label on the 3-day CARs and CMARs as well as potential non-linearities in the impact of SRISK on the CARs and CMARs. G-SIFI is a dummy variable indicating the institutions that are labelled as G-SIFIs by the FSB. Term_Spread is the difference between 10-year and 3-month treasury bill yields. We assume the yield curve is "flattening" whenever the term spread is below its sample mean. SRISK_flat_yc is the interaction term between SRISK and a flattening yield curve. SRISK_PS is the interaction term between SRISK and positive surprises. Lastly, SurpComp_flat_yc is the interaction term between the surprise component and a flattening yield curve. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01*

4.2.6. Focusing on depository institutions

Our analysis so far has been based on a holistic approach towards the financial sector, as our sample includes firms from all subsectors of the financial industry. Although we do control for the different subsectors, there might still be specific characteristics within each subsector that affect our results. To gain a deeper insight into the relationship we have observed so far, we run additional tests with a subsample including depository institutions only. We chose to focus on the depository institutions as these institutions are more likely to be affected by the interest rate changes due to the nature of their business. Claessens, Coleman, and Donnelly (2018) highlight the importance of low-interest-rate environment for banks and show that reductions in the interest rates lead to a drop in the net interest margin and squeezed profitability for banks. In our new regressions, we include four new interest rate- and financial distress-related control variables, as well as the controls used in the baseline regressions. The new variables are namely net interest margin (*NIM*), Federal funds purchased (*FFP*), interest-bearing deposits (*D_IB*), and non-performing assets (*NPA*).[25] By including these variables, we control for factors different than systemic risk that could affect the stock price reaction of depository institutions to interest rate changes.

Table 13 presents the results from the regressions estimated for the sample of depository institutions. Compared to our previous findings in **Table 8**, the most significant difference is the change sign of *SRISK* coefficient from negative to positive. This means that in the case for depository institutions, higher systemic risk has been associated with higher abnormal returns on the announcement dates in general. However, this finding does not contradict our previous interpretation based on the TBTF hypothesis. The TBTF hypothesis assumes that higher interest rates are bad news for the financial institutions, and the institutions with higher systemic risk exhibit a more positive (or a less negative) reaction to the rate increases. The results in **Table 13**, similar to our previous findings, show that the effect of *SurpComp* on the abnormal returns has been negative (in fact, this negative effect is stronger than for the aggregate sample). Furthermore, the interaction term between *SRISK* and the positive surprises shows that higher systemic risk has been associated with higher abnormal returns on the

[25] Description of the variables can be found in Appendix **3**.

announcement days with positive surprises. Therefore, these results provide further support to our narrative in the TBTF hypothesis.

Table 13 - The reaction of depository institutions

	(1)	*(2)*	*(3)*	*(4)*
	CAR(1, 1)	***CAR(1, 1)***	***CMAR(1, 1)***	***CMAR(1, 1)***
SRISK	**0.00036**	**0.00036**	**0.00031**	**0.00031**
	(2.53)**	(2.48)**	(1.70)*	(1.65)*
SRISK_flat_yc	**-0.00007**	**-0.00006**	**-0.00005**	**-0.00005**
	(0.87)	(0.77)	(0.68)	(0.60)
SRISK_PS	**0.00021**	**0.00018**	**0.00013**	**0.00010**
	(2.89)***	(2.71)***	(1.95)*	(1.61)
NIM	0.00078	0.00066	0.00043	0.00033
	(0.39)	(0.33)	(0.26)	(0.20)
FFP	-0.00000	-0.00000	-0.00000	-0.00000
	(0.82)	(0.80)	(1.07)	(1.04)
D_IB	-0.00000	-0.00000	-0.00000	-0.00000
	(3.39)***	(3.49)***	(0.80)	(0.87)
NPA	-0.00000	-0.00000	-0.00000	-0.00000
	(1.25)	(1.21)	(1.28)	(1.24)
SurpComp	**-0.03762**	**0.00892**	**-0.03634**	**0.00685**
	(3.52)***	(0.51)	(3.09)***	(0.39)
SurpComp_flat_yc		**-0.06519**		**-0.06046**
		(3.55)***		(3.22)***
Term_Spread	0.00333	0.00409	0.00198	0.00268
	(1.02)	(1.28)	(0.59)	(0.81)
Flat_yc	0.00173	0.00182	-0.00116	-0.00107
	(0.34)	(0.37)	(0.18)	(0.17)
Market_Cap	0.00714	0.00701	0.00539	0.00530
	(3.17)***	(3.05)***	(2.38)**	(2.27)**
MtB	-0.00032	-0.00046	0.00115	0.00104
	(0.15)	(0.22)	(0.54)	(0.49)
Rate_Hike	-0.00110	-0.00120	-0.00450	-0.00466
	(0.32)	(0.35)	(1.11)	(1.15)
Rate_Cut	-0.00851	-0.01712	-0.00526	-0.01325
	(1.73)*	(3.85)***	(1.06)	(3.07)***
Subprime	-0.00387	-0.00249	-0.00144	-0.00015
	(0.78)	(0.52)	(0.26)	(0.03)
Global	-0.04111	-0.02496	-0.04281	-0.02778
	(2.04)**	(1.17)	(1.86)*	(1.14)
Postcrisis	-0.04136	-0.02604	-0.04581	-0.03151
	(1.93)*	(1.14)	(1.90)*	(1.23)
_cons	-0.05488	-0.05229	-0.07669	-0.07413
	(2.10)**	(1.97)**	(1.87)*	(1.77)*
N	1,040	1,040	1,044	1,044

*Notes: The table presents the panel data regression results of the estimated CARs and CMARs. The sample only includes depository institutions and the regressions test for the effect of yield curve data and bank-specific variables on the 3-day CARs and CMARs as well as potential non-linearities in the impact of SRISK on the CARs and CMARs. 'NIM', 'FFP', 'D_IB' and 'NPA' are bank-specific variables, which denote net interest margin, Federal funds purchased, interest bearing deposits and non-performing assets respectively. Term_Spread is the difference between 10-year and 3-month treasury bill yields. We assume the yield curve is "flattening" whenever the term spread is below its sample mean. SRISK_flat_yc is the interaction term between SRISK and a flattening yield curve. SRISK_PS is the interaction term between SRISK and positive surprises. Lastly, SurpComp_flat_yc is the interaction term between the surprise component and a flattening yield curve. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01*

With regards to the yield curve, unlike the previous results, the results related to the depository institutions do not suggest a significant impact of the yield curve on the depository institutions' abnormal returns or on the effect of *SRISK* on the abnormal returns. Therefore, the short-term rates seem to be the main player in the relationship between monetary policy, systemic risk and the abnormal returns in the case for depository institutions. However, interacting the surprise component with the flat yield curve dummy indicates that the negative effect of surprise component on the abnormal returns is significantly stronger when the yield curve is relatively flat.

4.3. Placebo tests

To understand whether our results are capturing the price reaction to the monetary policy announcement rather than other confounding events, we run the panel data regression models on CARs and CMARs calculated on "placebo event" days, that is, days for which there are no monetary policy announcements. In particular, we consider days which are 5 trading days before the actual events. Since we are using daily data for *SRISK*, the models we run are as follows:

$$CAR_{i,t-5} = \alpha + \beta_1 SRISK_{i,t-5} + \varepsilon_{i,t-5} \tag{23}$$

$$CMAR_{i,t-5} = \alpha + \beta_1 SRISK_{i,t-5} + \varepsilon_{i,t-5} \tag{24}$$

$$\begin{aligned} CAR_{i,t-5} = {} & \alpha + \beta_1 SRISK_{i,t-5} + \beta_2 Market\_Cap_{i,t-5} + \beta_3 MtB_{i,t-5} + \beta_4 SurpComp_{t-5} \\ & + \theta_1 Rate\_Cut_t + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_{t-5} + \gamma_2 Global_{t-5} \\ & + \gamma_3 PostCrisis_{t-5} + \lambda FirmType_i + \varepsilon_{i,t-5} \end{aligned} \tag{25}$$

$$\begin{aligned} CMAR_{i,t-5} = {} & \alpha + \beta_1 SRISK_{i,t-5} + \beta_2 Market\_Cap_{i,t-5} + \beta_3 MtB_{i,t-5} + \beta_4 SurpComp_{t-5} + \\ & \theta_1 Rate\_Cut_t + \theta_2 Rate\_Hike_t + \gamma_1 Subprime_{t-5} + \gamma_2 Global_{t-5} + \\ & \gamma_3 PostCrisis_{t-5} + \lambda FirmType_i + \varepsilon_{i,t-5} \end{aligned} \tag{26}$$

The subscript *t* refers to the announcement day *t* from the 147 FOMC announcement days. Hence $CAR_{i,t-5}$ and $CMAR_{i,t-5}$ refer to the CARs and CMARs of firm *i* estimated five trading days prior to the actual events. The estimation window is (-260, -5) and the event window used is (-1, +1). In a similar manner, $SRISK_{i,t-5}$, $Market\_Cap_{i,t-5}$ *and* $MtB_{i,t-5}$ are equal to the *SRISK* index value, market capitalisation and the market to book ratio of firm *i* on day *t-5* which is five trading days before the event day *t*. The variable *SurpComp*$_{t-5}$ is a 'placebo' surprise component which is calculated on the placebo event day *t-5.* Although no announcement takes place on day *t-5,* it is still possible to estimate the changes in the Fed fund rate expectations based on the Kuttner (2001) approach, as follows:

$$SurpComp_{t-5} = \frac{D}{D-(t-5)}\left(f^{0}_{m,t-5} - f^{0}_{m,(t-5)-1}\right) \quad (27)$$

where $f^{0}_{m,t-5}$ is the current-month Fed funds futures rate on day *t-5* (5 trading date before the event date) and $f^{0}_{m,(t-5)-1}$ is the same rate on the previous day. The variable *D* is the total number of days in the month.

The placebo surprise component is included in the model to test weather regardless of monetary policy changes, the changes in Fud funds rate expectations can affect the abnormal returns of financial stocks on non-announcement days.

Importantly, unlike the rest of the variables, the dummy variables, *Rate_Cut* and *Rate_Hike*, are based on the actual announcement days and not the placebo event days. So *Rate_Cut* is equal to 1 if the announcement that takes place 5 days after the placebo event *t-5* is a rate cut and zero otherwise. Similarly, *Rate_Hike* is equal to 1 whenever the actual announcement following the placebo event is a rate increase announcement and zero otherwise. In so doing, we control for any significant increase in the abnormal returns of the financial firms on the days prior to the announcements of expansionary or tightening monetary policies. This could also be considered a test for potential news leakages or the predictions of the market.

The three variables, *Subprime, Global* and *Postcrisis* control for the two phases of the 2007-2009 financial crisis and the post crisis period as explained earlier.

Table 14 summarise the results for the estimation of the models presented in equations (23) to (26). The results show that, unlike the case for the FOMC announcement days, systemic risk is not a significant determinant of the CARs and the CMARs of the financial firms on non-announcement days.

These results suggest that our results are not driven by chance or a systematic relationship between CARs and systemic risk.

Table 14 – Regressions of the placebo CARs and CMARs

	CAR(-1, +1)		*CMAR(-1, +1)*	
	No Control	*Including Controls*	*No Control*	*Including Controls*
SRISK	**0.00001**	**0.00001**	**-0.00002**	**-0.00001**
	(0.91)	(0.57)	(0.95)	(0.35)
Market_Cap		-0.00012		-0.00014
		(0.46)		(0.47)
MtB		-0.00024		0.00010
		(1.66)*		(0.63)
SurpComp		-0.00615		-0.00433
		(0.85)		(0.57)
Rate_Hike		0.00025		0.00579
		(0.25)		(4.72)***
Rate_Cut		-0.00009		-0.00057
		(0.07)		(0.43)
Subprime		-0.00313		-0.00342
		(2.02)**		(2.22)**
Global		-0.00492		-0.01690
		(1.34)		(4.43)***
Postcrisis		-0.00566		-0.00937
		(1.11)		(1.94)*
Depository		0.00223		0.00226
		(2.62)***		(2.63)***
Non_Dep_CI		0.00227		0.00163
		(1.48)		(1.21)
BDES		0.00072		-0.00016
		(0.80)		(0.16)
Insurance		0.00182		0.00267
		(2.10)**		(2.96)***
_cons	0.00438	0.00580	0.01904	0.01828
	(3.15)***	(1.23)	(11.76)***	(3.53)***
N	11,675	11,658	11,929	11,898
R^2	0.0081	0.0095	0.0224	0.0299

*Notes: The table summarises the results from regressions of the placebo CARs and CMARs on SRISK and a set of firm- and event-specific control variables. The CARs are based on (-260, -5) estimation windows and both CARs and CMARs are estimated over (-1, +1) event windows on the days of placebo events that are assumed to be 5 trading days before the actual FOMC announcements. Therefore, there are 147 placebo event dates each corresponding with an actual FOMC announcement day that took place from 01/01/2000 to 31/12/2015. The first and the third columns represent the results from estimating equations (23) and (24) respectively. The second and the fourth columns provide the results from estimating equations (25) and (26). The models are estimated using random effects panel data regressions controlling for year fixed effects. The standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

5. Study limitations and further research

In this study we aimed to investigate the dynamics between financial institutions' systemic risk and their stock price reaction to monetary policy changes. While we employed a wide range of analyses and methodologies, there are still potential limitation to our research that should be noted. Firstly, as previous research and our results indicate, the reaction of financial stocks to monetary policy announcements tends to be state-dependant. Therefore, the inferences we make based on the analyses of our sample period might not perfectly reflect the dynamics of this relationship in other times. Although we tried to have a comprehensive sample period that covers the pre-crisis, crisis and post-crisis periods, a further analysis of the post-crisis period specifically can be useful to help us gain a more in-depth understanding of the current environment.

Second, our focus in this paper is on conventional monetary policy and interest rate decisions. Although we do control for the crisis and the ZLB periods in our analysis, a specific study based on the unconventional monetary policies introduced during the crisis and post-crisis periods could lead to important findings. Such a study can potentially provide further support to our explained TBTF hypothesis, as well as providing us with a useful evaluation of the unconventional monetary policies.

6. Concluding remarks

In this paper, we have employed an event study methodology to investigate the relationship between systemic risk and announcements related to conventional monetary policy in the US financial system. For this purpose, we run multiple tests to see if the reaction of financial institutions with high systemic risk is different to that of the institutions with low systemic risk, whenever there is an unexpected change to the short-term interest rates. Our main results show that systemic risk tends to increase (reduce) abnormal returns for announcements related to a positive (negative) unexpected change in the target rate.

We also find that institutions with high systemic risk tend to have relatively higher abnormal returns than those with low systemic risk when the yield curve on the announcement date is relatively flat. Previous literature suggests that higher interest rates and a flatter yield curve are associated with an increased likelihood of an upcoming recession (Ang, Piazzesi, and Wei 2006). In our regression analysis, we also find support for these arguments. Therefore, our interpretations of our results are based on the assumption that higher short-term rates and a flat yield curve are considered bad news for the financial stocks. This effect is more prominent when we focus on depository institutions only, instead of the entire financial system.

Thus, we explain our results based on a TBTF narrative. Systemically important institutions are believed to benefit from implicit public guarantees and tend to be less exposed to tail risk (Gandhi and Lustig 2015). Whenever the sovereign credit risk increases, these institutions face significant equity value losses (Correa et al. 2014). Therefore, these institutions react better than those with low systemic risk to monetary policy announcements that might lead to a higher distress risk in the financial system. An important finding here is that the quantitively measured level of systemic risk is of more importance the stock market participants, than the so-called TBTF label. Although the effect of the TBTF label is in the same direction to that of systemic risk level, our findings suggest that the effect of the latter is more significant.

These results are important because they suggest that conventional monetary policy might indirectly affect the market for financial stocks, because investors tend to buy stocks with high systemic risk if interest rates are higher than expected, or the yield curve becomes flatter. It can therefore be argued that the government guarantees and bailout plans provided *ex-post* to the TBTF institutions help these institutions stay better capitalised *ex-ante* in riskier times.

Our findings also imply that the market's evaluation of systemic risk changes according to the macro state. Like other forms of risk, systemic risk typically reduces the abnormal returns of the financial institutions (as it is determined by a firm's size, leverage ratio and correlation with the market). However, upon increased risk of economic slowdown and uncertainty, higher systemic risk is seen as an indication a safe-haven investment. This shows that the market trusts that the TBTF institutions are more likely to be rescued by the authorities in the event of a systemic crisis.

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Appendices

1. Sample details:

1.1. List of the sample financial institutions:

1. Wachovia
2. Bear Stearns
3. Compass Bancshares
4. Chubb Ltd
5. AMBAC Financial
6. American Capital Ltd
7. Aetna Inc
8. Aflac Inc
9. A.G. Edwards
10. American International Group Inc
11. Assurant Inc
12. Allstate Corp/The
13. Ameriprise Financial Inc
14. TD Ameritrade Holding Corp
15. Aon PLC
16. American Express Co
17. Bank of America Corp
18. BB&T Corp
19. Franklin Resources Inc
20. Bank of New York Mellon Corp/The
21. BlackRock Inc
22. CBOT Holdings
23. Berkshire Hathaway Inc
24. CBRE Group Inc
25. Commerce Bancshares Inc/MO
26. Countrywide Financial
27. Cincinnati Financial Corp
28. CIT Group Inc
29. Cigna Corp
30. Comerica Inc
31. CME Group Inc/IL
32. CNA Financial Corp
33. Capital One Financial Corp
34. Coventry Health Care
35. Citigroup Inc
36. E*TRADE Financial Corp
37. Eaton Corp PLC
38. Eaton Vance Corp
39. Fifth Third Bancorp
40. FNF Group
41. Fannie Mae*
42. Freddie Mac*
43. Genworth Financial Inc
44. Goldman Sachs Group Inc/The
45. Huntington Bancshares Inc/OH
46. Hudson City Bancorp Inc
47. Hartford Financial Services Group Inc/The
48. Health Net Inc/Old
49. H&R Block Inc
50. Humana Inc
51. Intercontinental Exchange Inc
52. Janus Capital Group Inc
53. JPMorgan Chase & Co
54. KeyCorp
55. Lehman Brothers
56. Legg Mason Inc
57. Lincoln National Corp
58. MBIA Inc
59. Merrill Lynch
60. MetLife Inc
61. Marshall & Ilsley
62. Marsh & McLennan Cos Inc
63. Morgan Stanley
64. M&T Bank Corp
65. National City Corporation
66. NYMEX
67. Northern Trust Corp
68. New York Community Bancorp Inc
69. NYSE Euronext
70. People's United Financial Inc
71. Principal Financial Group Inc
72. Progressive Corp/The
73. PNC Financial Services Group Inc/The
74. Prudential Financial Inc
75. Regions Financial Corp
76. Safeco
77. Charles Schwab Corp/The
78. SEI Investments Co
79. SLM Corp
80. Synovus Financial Corp
81. Sovereign Bank
82. SunTrust Banks Inc
83. State Street Corp
84. Torchmark Corp
85. T Rowe Price Group Inc
86. Travelers Cos Inc/The
87. UnionBanCal
88. UnitedHealth Group Inc
89. Unum Group
90. US Bancorp
91. Washington Mutual
92. Wells Fargo & Co
93. WR Berkley Corp
94. Western Union Co/The
95. Zions Bancorporation

1.2. Sample financial institutions Vs the total US financial sector

Table A.1 - Comparison of the study sample and the aggregate US financial sector

Year	*Sample Total Cap*	*Sector Total Cap*	*Ratio*
2000	1885.17	3248.53	58.03%
2001	1796.27	3048.77	58.92%
2002	1509.32	2812.55	53.66%
2003	1979.27	3747.87	52.81%
2004	2310.79	4326.71	53.41%
2005	2465.26	4700.05	52.45%
2006	2940.33	5671.07	51.85%
2007	2385.13	4876.91	48.91%
2008	1093.77	2768.83	39.50%
2009	1460.56	3742.36	39.03%
2010	1774.02	4522.22	39.23%
2011	1447.64	4199.29	34.47%
2012	1778.64	5219.35	34.08%
2013	2508.26	6764.06	37.08%
2014	2791.72	7660.48	36.44%
2015	2455.41	7460.28	32.91%
		Average	**45.17%**

Notes: The table presents a comparison between the aggregate end-of-year market capitalisations of the sample firms in this study (second column) and the entire US financial sector (third column), during our sample period. The last column shows the ratio of the sample market cap to the total US financial sector market cap.

2. *FOMC announcements under study:*

Table A.2 – List of the FOMC Fed funds target rate announcements in the sample period

Announcement Date	*Target rate (Upper bound)*	*Target rate (Lower bound)*	*Event type*	*Policy type*
16 May 2000	6.5000	N/A	Meeting	Rate hike
28 June 2000	6.5000	N/A	Meeting	Unchanged rate
22 August 2000	6.5000	N/A	Meeting	Unchanged rate
03 October 2000	6.5000	N/A	Meeting	Unchanged rate
15 November 2000	6.5000	N/A	Meeting	Unchanged rate
19 December 2000	6.5000	N/A	Meeting	Unchanged rate
03 January 2001	6.0000	N/A	Conference Call	Rate cut
31 January 2001	5.5000	N/A	Meeting	Rate cut
20 March 2001	5.0000	N/A	Meeting	Rate cut
11 April 2001	5.0000	N/A	Conference Call	Unchanged rate
18 April 2001	4.5000	N/A	Conference Call	Rate cut
15 May 2001	4.0000	N/A	Meeting	Rate cut
27 June 2001	3.7500	N/A	Meeting	Rate cut
21 August 2001	3.5000	N/A	Meeting	Rate cut
13 September 2001	3.5000	N/A	Conference Call	Unchanged rate
02 October 2001	2.5000	N/A	Meeting	Rate cut
06 November 2001	2.0000	N/A	Meeting	Rate cut
11 December 2001	1.7500	N/A	Meeting	Rate cut
30 January 2002	1.7500	N/A	Meeting	Unchanged rate
19 March 2002	1.7500	N/A	Meeting	Unchanged rate
07 May 2002	1.7500	N/A	Meeting	Unchanged rate
26 June 2002	1.7500	N/A	Meeting	Unchanged rate
13 August 2002	1.7500	N/A	Meeting	Unchanged rate
24 September 2002	1.7500	N/A	Meeting	Unchanged rate
06 November 2002	1.2500	N/A	Meeting	Rate cut
10 December 2002	1.2500	N/A	Meeting	Unchanged rate
29 January 2003	1.2500	N/A	Meeting	Unchanged rate
18 March 2003	1.2500	N/A	Meeting	Unchanged rate
25 March 2003	1.2500	N/A	Conference Call	Unchanged rate
01 April 2003	1.2500	N/A	Conference Call	Unchanged rate
08 April 2003	1.2500	N/A	Conference Call	Unchanged rate
16 April 2003	1.2500	N/A	Conference Call	Unchanged rate
06 May 2003	1.2500	N/A	Meeting	Unchanged rate
25 June 2003	1.0000	N/A	Meeting	Rate cut
12 August 2003	1.0000	N/A	Meeting	Unchanged rate
16 September 2003	1.0000	N/A	Meeting	Unchanged rate
28 October 2003	1.0000	N/A	Meeting	Unchanged rate
09 December 2003	1.0000	N/A	Meeting	Unchanged rate
28 January 2004	1.0000	N/A	Meeting	Unchanged rate
16 March 2004	1.0000	N/A	Meeting	Unchanged rate
04 May 2004	1.0000	N/A	Meeting	Unchanged rate
30 June 2004	1.2500	N/A	Meeting	Rate hike
10 August 2004	1.5000	N/A	Meeting	Rate hike
21 September 2004	1.7500	N/A	Meeting	Rate hike
10 November 2004	2.0000	N/A	Meeting	Rate hike
14 December 2004	2.2500	N/A	Meeting	Rate hike
02 February 2005	2.5000	N/A	Meeting	Rate hike
22 March 2005	2.7500	N/A	Meeting	Rate hike
03 May 2005	3.0000	N/A	Meeting	Rate hike
30 June 2005	3.2500	N/A	Meeting	Rate hike
09 August 2005	3.5000	N/A	Meeting	Rate hike
20 September 2005	3.7500	N/A	Meeting	Rate hike
01 November 2005	4.0000	N/A	Meeting	Rate hike
13 December 2005	4.2500	N/A	Meeting	Rate hike
31 January 2006	4.5000	N/A	Meeting	Rate hike
28 March 2006	4.7500	N/A	Meeting	Rate hike
10 May 2006	5.0000	N/A	Meeting	Rate hike
29 June 2006	5.2500	N/A	Meeting	Rate hike
08 August 2006	5.2500	N/A	Meeting	Unchanged rate

20 September 2006	5.2500	N/A	Meeting	Unchanged rate
25 October 2006	5.2500	N/A	Meeting	Unchanged rate
12 December 2006	5.2500	N/A	Meeting	Unchanged rate
31 January 2007	5.2500	N/A	Meeting	Unchanged rate
21 March 2007	5.2500	N/A	Meeting	Unchanged rate
09 May 2007	5.2500	N/A	Meeting	Unchanged rate
28 June 2007	5.2500	N/A	Meeting	Unchanged rate
07 August 2007	5.2500	N/A	Meeting	Unchanged rate
10 August 2007	5.2500	N/A	Conference Call	Unchanged rate
16 August 2007	5.2500	N/A	Conference Call	Unchanged rate
18 September 2007	4.7500	N/A	Meeting	Rate cut
31 October 2007	4.5000	N/A	Meeting	Rate cut
06 December 2007	4.5000	N/A	Conference Call	Unchanged rate
11 December 2007	4.2500	N/A	Meeting	Rate cut
09 January 2008	4.2500	N/A	Conference Call	Unchanged rate
22 January 2008	3.5000	N/A	Conference Call	Rate cut
30 January 2008	3.0000	N/A	Meeting	Rate cut
10 March 2008	3.0000	N/A	Conference Call	Unchanged rate
18 March 2008	2.2500	N/A	Meeting	Rate cut
30 April 2008	2.0000	N/A	Meeting	Rate cut
25 June 2008	2.0000	N/A	Meeting	Unchanged rate
24 July 2008	2.0000	N/A	Conference Call	Unchanged rate
05 August 2008	2.0000	N/A	Meeting	Unchanged rate
29 September 2008	2.0000	N/A	Conference Call	Unchanged rate
08 October 2008	1.5000	N/A	Conference Call	Rate cut
29 October 2008	1.0000	N/A	Meeting	Rate cut
16 December 2008	0.25	0.00	Meeting	Rate cut
16 January 2009	0.25	0.00	Conference Call	Unchanged rate
28 January 2009	0.25	0.00	Meeting	Unchanged rate
07 February 2009	0.25	0.00	Conference Call	Unchanged rate
18 March 2009	0.25	0.00	Meeting	Unchanged rate
29 April 2009	0.25	0.00	Meeting	Unchanged rate
03 June 2009	0.25	0.00	Conference Call	Unchanged rate
24 June 2009	0.25	0.00	Meeting	Unchanged rate
12 August 2009	0.25	0.00	Meeting	Unchanged rate
23 September 2009	0.25	0.00	Meeting	Unchanged rate
04 November 2009	0.25	0.00	Meeting	Unchanged rate
16 December 2009	0.25	0.00	Meeting	Unchanged rate
27 January 2010	0.25	0.00	Meeting	Unchanged rate
16 March 2010	0.25	0.00	Meeting	Unchanged rate
28 April 2010	0.25	0.00	Meeting	Unchanged rate
09 May 2010	0.25	0.00	Conference Call	Unchanged rate
23 June 2010	0.25	0.00	Meeting	Unchanged rate
10 August 2010	0.25	0.00	Meeting	Unchanged rate
21 September 2010	0.25	0.00	Meeting	Unchanged rate
15 October 2010	0.25	0.00	Conference Call	Unchanged rate
03 November 2010	0.25	0.00	Meeting	Unchanged rate
14 December 2010	0.25	0.00	Meeting	Unchanged rate
26 January 2011	0.25	0.00	Meeting	Unchanged rate
15 March 2011	0.25	0.00	Meeting	Unchanged rate
27 April 2011	0.25	0.00	Meeting	Unchanged rate
22 June 2011	0.25	0.00	Meeting	Unchanged rate
01 August 2011	0.25	0.00	Conference Call	Unchanged rate
09 August 2011	0.25	0.00	Meeting	Unchanged rate
21 September 2011	0.25	0.00	Meeting	Unchanged rate
02 November 2011	0.25	0.00	Meeting	Unchanged rate
28 November 2011	0.25	0.00	Conference Call	Unchanged rate
13 December 2011	0.25	0.00	Meeting	Unchanged rate
25 January 2012	0.25	0.00	Meeting	Unchanged rate
13 March 2012	0.25	0.00	Meeting	Unchanged rate
25 April 2012	0.25	0.00	Meeting	Unchanged rate
20 June 2012	0.25	0.00	Meeting	Unchanged rate
01 August 2012	0.25	0.00	Meeting	Unchanged rate
13 September 2012	0.25	0.00	Meeting	Unchanged rate
24 October 2012	0.25	0.00	Meeting	Unchanged rate
12 December 2012	0.25	0.00	Meeting	Unchanged rate
30 January 2013	0.25	0.00	Meeting	Unchanged rate

20 March 2013	0.25	0.00	Meeting	Unchanged rate
01 May 2013	0.25	0.00	Meeting	Unchanged rate
19 June 2013	0.25	0.00	Meeting	Unchanged rate
31 July 2013	0.25	0.00	Meeting	Unchanged rate
18 September 2013	0.25	0.00	Meeting	Unchanged rate
30 October 2013	0.25	0.00	Meeting	Unchanged rate
18 December 2013	0.25	0.00	Meeting	Unchanged rate
29 January 2014	0.25	0.00	Meeting	Unchanged rate
19 March 2014	0.25	0.00	Meeting	Unchanged rate
30 April 2014	0.25	0.00	Meeting	Unchanged rate
18 June 2014	0.25	0.00	Meeting	Unchanged rate
30 July 2014	0.25	0.00	Meeting	Unchanged rate
17 September 2014	0.25	0.00	Meeting	Unchanged rate
29 October 2014	0.25	0.00	Meeting	Unchanged rate
17 December 2014	0.25	0.00	Meeting	Unchanged rate
28 January 2015	0.25	0.00	Meeting	Unchanged rate
18 March 2015	0.25	0.00	Meeting	Unchanged rate
29 April 2015	0.25	0.00	Meeting	Unchanged rate
17 June 2015	0.25	0.00	Meeting	Unchanged rate
29 July 2015	0.25	0.00	Meeting	Unchanged rate
17 September 2015	0.25	0.00	Meeting	Unchanged rate
28 October 2015	0.25	0.00	Meeting	Unchanged rate
16 December 2015	0.50	0.25	Meeting	Rate hike

Notes: The table presents the details about each FOMC Fed funds target rate announcements investigated in this study. The current target rate announcement system with the lower and upper bounds was introduced in December 2008, therefore, the announcements prior to that date are represented by a single rate.

3. *Variable descriptions*

Table A.3 – Description of the variables used in the study

Variable	*Symbol*	*Description*
Cumulative abnormal return	CAR	Cumulative abnormal return of the firm over the specific event window estimated using a market model over a 250-day estimation window which ends 5 days before the event date.
Cumulative market adjusted return	CMAR	Cumulative market-adjusted return of the firm over the specific event window. The market-adjusted return is calculated as the difference between the stock return and the aggregate market return.
Systemic risk	SRISK	The financial institutions systemic risk measure estimated based on the V. Acharya et al. (2012) approach.
Market capitalisation	Market_Cap	Total equity value of the firm in the stock market.
Market-to-book Ratio	MtB	Ratio of the market value to book value of the firm's equity.
Surprise component	SurpComp	Unexpected component of the announced Fed funds target rate by the FOMC, calculated based on the method introduced by Kuttner (2001).
Interest rate hike	Rate_Hike	Dummy variable indicating the announcement of a target rate hike.
Interest rate cut	Rate_Cut	Dummy variable indicating the announcement of a target rate cut.
Crisis period – subprime phase	Subprime	Dummy variable indicating the subprime phase of the financial crisis, which starts from 01/06/2007 and ends on 14/09/2008.
Crisis period – global phase	Global	Dummy variable indicating the global phase of the financial crisis, which starts from 15/09/2008 and ends on 31/03/2009.
Post crisis period	Postcrisis	Dummy variable indicating the post-crisis period, starting from 01/04/2009 until the end of the sample period (31/12/2015).
Depository institutions	Depository	Dummy variable indicating the depository institutions, which have SIC codes starting by 60.
Non-depository credit institutions	Non_Dep_CI	Dummy variable indicating the non-depository credit institutions, which have SIC codes starting by 61.
Broker-dealers and exchange services	BDES	Dummy variable indicating broker-dealers and exchange services, which have SIC codes starting by 62.
Insurance companies	Insurance	Dummy variable indicating insurance companies, which have SIC codes starting by 63 or 64.
Interaction between systemic risk and yield curve slope	SRISK_flat_yc	Interaction term between SRISK index and a dummy variable identifying "flattening yield curve". The yield curve is assumed to be flattening whenever the "term spread" is below its sample mean.
Interaction between systemic risk and positive surprises	SRISK_PS	Interaction term between SRISK index and the days of FOMC announcements related to "positive surprises".
Term spread	Term_Spread	The spread between the yields of 10-year Treasury Bonds and 3-month Treasury Bills.
Interaction between the surprise component and yield curve slope	SurpComp_flat_yc	Interaction term between the "surprise component" and a dummy variable identifying "flattening yield curve". The yield curve is assumed to be flattening whenever the "term spread" is below its sample mean.
Interaction between systemic risk and the crisis period	SRISK_Crisis	Interaction term between the SRISK index and the crisis period (defined as 01/06/2007 until 31/03/2009)
CRSP value weighted index	CRSPVW	CRSP value weighted aggregate market index.
Positive surprise announcements	Positive_Surp	Dummy variable identifying the FOMC announcement days when the announced target rate is higher than the markets expectation.
Negative surprise announcements	Negative_Surp	Dummy variable identifying the FOMC announcement days when the announced target rate is lower than the markets expectation.

Global Systemically Important Financial Institution	G-SIFI	Dummy variable indicating financial institutions that are classified as Global Systemically Important Financial Institution by the Financial Stability Board.
Net Interest Margin	*NIM*	Difference between the bank's total interest income and total interest expense, relative to the assets value.
Federal funds purchased	*FFP*	Total funds borrowed in the Federal funds market (from other banks).
Interest-bearing Deposits	*D_IB*	Total customer deposits that are subject to interest payments by the bank.
Non-performing assets	*NPA*	Total value of loans and advances that are in default or in arrears.

4. *Key information on the 147 FOMC announcements under study*

Table A.4 – Statistical details of the announced target rates and the sample firms' stock price reaction

Date	*No of firms*	*Mean CAR*	*Mean SR*	*Rate change*	*Surprise component*	*Expected change*	*ADJ-BMP*
21/03/2000	18	0.0455***	0.1235	0.25	-0.0620	0.3120	3.0025
16/05/2000	58	0.0089	0.0175	0.5	0.0827	0.4173	0.6096
28/06/2000	59	0.0111	0.0512	0	-0.0200	0.0200	1.1150
22/08/2000	77	-0.0021	-0.0370	0	0.0000	0.0000	-0.4849
03/10/2000	79	0.0022	0.0075	0	0.0000	0.0000	0.3400
15/11/2000	79	-0.0093	-0.0128	0	0.0000	0.0000	-1.2163
19/12/2000	78	0.0496***	0.0518	0	0.1421	-0.1421	5.6822
03/01/2001	79	-0.0208	-0.0135	-0.5	-0.3211	-0.1789	-1.2435
31/01/2001	79	-0.0104	-0.0292	-0.5	0.0050	-0.5050	-1.5045
20/03/2001	79	-0.0266***	-0.0301	-0.5	0.0705	-0.5705	-4.4895
11/04/2001	79	-0.0060	-0.0105	0	0.0868	-0.0868	-1.1127
18/04/2001	79	-0.0160*	-0.0149	-0.5	-1.0500	0.5500	-1.9584
15/05/2001	79	0.0041	0.0085	-0.5	-0.1453	-0.3547	1.2558
27/06/2001	80	0.0003	-0.0016	-0.25	0.8500	-1.1000	-0.1122
21/08/2001	80	0.0045	0.0058	-0.25	0.0620	-0.3120	0.4773
02/10/2001	80	-0.0070	-0.0081	-0.5	-0.0909	-0.4091	-0.7691
06/11/2001	80	0.0156***	0.0301	-0.5	-0.1313	-0.3687	2.7611
11/12/2001	80	-0.0053	-0.0150	-0.25	0.0155	-0.2655	-1.2518
30/01/2002	81	-0.0048	-0.0090	0	0.0150	-0.0150	-1.3769
19/03/2002	81	-0.0053*	-0.0209	0	-0.0517	0.0517	-1.9213
07/05/2002	82	-0.0102***	-0.0133	0	0.0000	0.0000	-2.9383
26/06/2002	82	0.0020	0.0019	0	-0.1500	0.1500	0.2155
13/08/2002	82	0.0000	-0.0016	0	0.0517	-0.0517	-0.1924
24/09/2002	82	-0.0026	-0.0029	0	0.1000	-0.1000	-0.3645
06/11/2002	82	-0.0219***	-0.0606	-0.5	-0.2000	-0.3000	-3.9166
10/12/2002	82	0.0046	0.0140	0	0.0000	0.0000	1.3709
29/01/2003	82	-0.0042*	-0.0136	0	0.0050	-0.0050	-1.7749
18/03/2003	83	0.0084	0.0081	0	0.0596	-0.0596	1.1934
25/03/2003	83	0.0004	-0.0036	0	0.0000	0.0000	-0.4968
01/04/2003	83	0.0053*	0.0097	0	-0.1086	0.1086	1.6817
08/04/2003	83	-0.0034	-0.0292	0	-0.0136	0.0136	-1.4554
16/04/2003	83	0.0011	0.0002	0	0.0000	0.0000	0.0185
06/05/2003	83	0.0023	-0.0060	0	0.0186	-0.0186	-0.2649
25/06/2003	83	0.0028	0.0084	-0.25	0.7500	-1.0000	0.4877
12/08/2003	83	-0.0081***	-0.0512	0	0.0000	0.0000	-3.4197
16/09/2003	83	0.0044	0.0161	0	0.0000	0.0000	1.4381
28/10/2003	83	-0.0006	0.0019	0	0.0000	0.0000	0.0695
09/12/2003	83	-0.0056	-0.0131	0	0.0000	0.0000	-0.9804
28/01/2004	83	0.0024	0.0054	0	0.0000	0.0000	0.7096
16/03/2004	83	0.0019	0.0037	0	0.0000	0.0000	0.7566
04/05/2004	84	-0.0016	-0.0144	0	-0.0115	0.0115	-0.5707
30/06/2004	83	0.0013	0.0035	0.25	-0.0100	0.2600	0.4019
10/08/2004	84	0.0085***	0.0266	0.25	0.0295	0.2205	3.4440
21/09/2004	86	-0.0051*	-0.0143	0.25	0.0000	0.2500	-1.8049
10/11/2004	86	0.0039	0.0169	0.25	0.0075	0.2425	1.1688
14/12/2004	86	0.0000	-0.0023	0.25	0.0000	0.2500	-0.1779
02/02/2005	86	-0.0051	-0.0181	0.25	0.0000	0.2500	-1.2142
22/03/2005	86	-0.0060***	-0.0249	0.25	0.0000	0.2500	-2.6687
03/05/2005	86	0.0084*	0.0237	0.25	0.0055	0.2445	1.9017
30/06/2005	86	0.0019	0.0037	0.25	0.0000	0.2500	0.2779
09/08/2005	86	0.0030	0.0083	0.25	0.0000	0.2500	0.5722
20/09/2005	86	-0.0048***	-0.0154	0.25	0.1050	0.1450	-2.6132
01/11/2005	86	-0.0007	-0.0075	0.25	0.1552	0.0948	-0.6983
13/12/2005	86	-0.0014	0.0008	0.25	0.0000	0.2500	0.0265
31/01/2006	89	-0.0063***	-0.0919	0.25	0.0000	0.2500	-2.3491
28/03/2006	90	-0.0050***	-0.0231	0.25	0.0517	0.1983	-2.6749
10/05/2006	90	0.0021	0.0049	0.25	0.0000	0.2500	0.8196

29/06/2006	91	-0.0031	-0.0057	0.25	-0.0150	0.2650	-1.5188
08/08/2006	91	-0.0058**	-0.0352	0	-0.0539	0.0539	-2.2211
20/09/2006	91	0.0031*	0.0164	0	0.0000	0.0000	1.6499
25/10/2006	91	-0.0029	-0.0206	0	0.0000	0.0000	-0.8354
12/12/2006	91	0.0026*	0.0561	0	0.0000	0.0000	1.8869
31/01/2007	91	0.0015	0.0080	0	0.0000	0.0000	0.6095
21/03/2007	91	-0.0018	-0.0009	0	0.0000	0.0000	-0.1547
09/05/2007	91	0.0019	0.0017	0	0.0070	-0.0070	0.3025
28/06/2007	92	-0.0084***	-0.0499	0	0.0000	0.0000	-3.4993
07/08/2007	91	0.0228***	0.0604	0	0.0517	-0.0517	3.6597
10/08/2007	91	-0.0053	-0.0097	0	-0.0369	0.0369	-1.0715
16/08/2007	91	0.0395***	0.0725	0	-0.0827	0.0827	5.3901
18/09/2007	90	0.0082**	0.0145	-0.5	-0.4000	-0.1000	2.2417
31/10/2007	89	-0.0098	-0.0125	-0.25	-0.0200	-0.2300	-1.1674
06/12/2007	89	-0.0003	-0.0037	0	0.0248	-0.0248	-0.3056
11/12/2007	89	-0.0164***	-0.0258	-0.25	0.0155	-0.2655	-2.6119
09/01/2008	89	0.0026	0.0045	0	-0.0282	0.0282	0.3476
22/01/2008	89	0.0723***	0.1117	-0.75	-1.7911	1.0411	3.4268
30/01/2008	89	0.0169*	0.0312	-0.5	-0.0950	-0.4050	1.7618
10/03/2008	89	0.0229	0.0240	0	-0.0295	0.0295	1.6438
18/03/2008	89	0.0241	0.0207	-0.75	0.5008	-1.2508	1.4517
30/04/2008	90	0.0217***	0.0521	-0.25	-0.0550	-0.1950	3.6600
25/06/2008	89	0.0162***	0.0222	0	-0.0600	0.0600	2.4881
24/07/2008	88	-0.0165	-0.0194	0	0.0000	0.0000	-1.0920
05/08/2008	88	0.0134	0.0119	0	-0.0060	0.0060	1.0325
29/09/2008	82	0.0355**	0.0154	0	-0.1000	0.1000	2.3084
08/10/2008	82	-0.0197	-0.0125	-0.5	-0.1685	-0.3315	-1.0800
29/10/2008	82	-0.0752***	-0.0234	-0.5	-0.0600	-0.4400	-2.3651
16/12/2008	81	0.0039	0.0030	-0.875	-0.3410	-0.5340	0.3636
16/01/2009	77	-0.0986***	-0.0689	0	0.0000	0.0000	-3.1577
28/01/2009	78	0.0397**	0.0257	0	0.0000	0.0000	2.2605
18/03/2009	77	0.0191	0.0104	0	-0.0238	0.0238	0.8715
29/04/2009	77	-0.0200*	-0.0271	0	-0.0050	0.0050	-1.6681
03/06/2009	77	0.0094	0.0188	0	0.0000	0.0000	1.2863
24/06/2009	77	-0.0171**	-0.0182	0	0.0000	0.0000	-2.2310
12/08/2009	77	-0.0095	-0.0092	0	-0.0082	0.0082	-0.8308
23/09/2009	77	-0.0061	-0.0133	0	-0.0214	0.0214	-1.0217
04/11/2009	77	-0.0220***	-0.0488	0	0.0000	0.0000	-2.9626
16/12/2009	77	0.0017	0.0105	0	-0.0310	0.0310	0.9554
27/01/2010	77	0.0179**	0.0270	0	0.0000	0.0000	2.2971
16/03/2010	77	0.0028	0.0136	0	0.0000	0.0000	0.6274
28/04/2010	77	0.0087*	0.0112	0	0.0000	0.0000	1.7134
23/06/2010	78	0.0039	0.0031	0	0.0000	0.0000	0.5030
10/08/2010	78	0.0009	0.0049	0	0.0000	0.0000	1.1108
21/09/2010	78	-0.0129***	-0.0393	0	-0.0167	0.0167	-3.6643
15/10/2010	78	-0.0034	-0.0286	0	0.0000	0.0000	-0.7601
03/11/2010	78	0.0056	0.0115	0	0.0000	0.0000	1.2922
14/12/2010	77	-0.0068*	-0.0336	0	0.0000	0.0000	-1.7244
26/01/2011	77	0.0018	0.0361	0	0.0000	0.0000	1.1027
15/03/2011	77	0.0062	0.0111	0	0.0000	0.0000	1.5826
27/04/2011	77	-0.0026	-0.0042	0	0.0000	0.0000	-0.1454
22/06/2011	77	-0.0121***	-0.0380	0	-0.0187	0.0187	-4.3221
01/08/2011	76	0.0049	0.0076	0	0.0207	-0.0207	1.2238
09/08/2011	76	-0.0223***	-0.0098	0	0.0000	0.0000	-2.9500
21/09/2011	76	0.0064	0.0097	0	0.0667	-0.0667	1.3693
02/11/2011	76	-0.0091*	-0.0145	0	0.0000	0.0000	-1.8917
28/11/2011	76	-0.0047	-0.0101	0	0.0000	0.0000	-1.2699
13/12/2011	76	0.0133***	0.0356	0	0.0000	0.0000	3.2902
25/01/2012	76	-0.0189***	-0.1156	0	0.0000	0.0000	-2.8006
13/03/2012	76	0.0148***	0.0538	0	0.0086	-0.0086	2.9383
25/04/2012	76	-0.0086	-0.0334	0	0.0300	-0.0300	-1.5529
20/06/2012	76	0.0128***	0.0298	0	0.0150	-0.0150	3.6995
01/08/2012	76	0.0031	0.0285	0	0.0000	0.0000	0.8329
13/09/2012	76	0.0050	0.0211	0	0.0000	0.0000	1.4975
24/10/2012	76	0.0055	0.0151	0	0.0000	0.0000	1.1563
12/12/2012	76	0.0024	0.0054	0	0.0000	0.0000	0.3511
30/01/2013	76	0.0053**	0.0304	0	0.0000	0.0000	2.0194

20/03/2013	76	-0.0047*	-0.0143	0	0.0000	0.0000	-1.9002
01/05/2013	76	-0.0007	-0.0049	0	0.0000	0.0000	-0.4192
19/06/2013	75	0.0188***	0.0253	0	0.0136	-0.0136	3.7253
31/07/2013	75	0.0081***	0.0383	0	0.0000	0.0000	3.0672
18/09/2013	75	-0.0216***	-0.0784	0	0.0000	0.0000	-3.5397
30/10/2013	75	-0.0013	-0.0034	0	0.0000	0.0000	-0.3021
18/12/2013	74	-0.0007	-0.0018	0	0.0000	0.0000	-0.2465
29/01/2014	74	0.0000	0.0018	0	0.0000	0.0000	0.3272
19/03/2014	74	0.0165***	0.0643	0	0.0000	0.0000	4.9977
30/04/2014	74	0.0049	0.0543	0	0.0000	0.0000	1.2704
18/06/2014	74	0.0028	0.0236	0	0.0000	0.0000	1.5952
30/07/2014	73	0.0009	0.0039	0	0.0000	0.0000	0.4499
17/09/2014	72	0.0037**	0.0299	0	0.0000	0.0000	2.2862
29/10/2014	74	0.0035*	0.0123	0	0.0050	-0.0050	1.6573
17/12/2014	74	-0.0019	-0.0018	0	0.0111	-0.0111	-0.7076
28/01/2015	74	-0.0038**	-0.0101	0	0.0000	0.0000	-2.1878
18/03/2015	74	-0.0129***	-0.0502	0	-0.0119	0.0119	-6.3686
29/04/2015	74	0.0132***	0.0481	0	0.0000	0.0000	4.0262
17/06/2015	74	-0.0090***	-0.0397	0	-0.0115	0.0115	-3.6813
29/07/2015	74	-0.0077***	-0.0288	0	0.0000	0.0000	-3.6767
17/09/2015	74	-0.0238***	-0.0819	0	-0.1154	0.1154	-8.6342
28/10/2015	74	0.0112***	0.0393	0	0.0000	0.0000	2.4586
16/12/2015	69	0.0061***	0.0149	0.25	0.0413	0.2087	2.8176

*Notes: The table summarises the information about all the Fed funds target rate announcements examined in this study and our sample financial institutions' reaction to them. Mean standardised CARs (Mean SR) and the ADJ-BMP statistic are calculated based on the procedure explained in section 3.2.1. 'Rate change' shows the announced target rate change, which is decomposed into 'Surprise component' and 'Expected component'. * $p<0.1$; ** $p<0.05$; *** $p<0.01$*

5. *Robustness Tests*

Table A.5 – Results for CAR panel data regressions: 1-day event window

CAR(0, 0)	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**0.00002**	**0.00011**	**-0.00001**	**0.00001**	**0.00009**	**-0.00001**	**0.00001**	**0.00001**
	(0.81)	(5.78)***	(1.02)	(0.37)	(5.03)***	(1.64)	(1.32)	(1.27)
Market_Cap				0.00018	-0.00017	0.00017	0.00007	0.00007
				(0.48)	(0.62)	(0.92)	(0.45)	(0.47)
MtB				-0.00003	0.00003	-0.00008	-0.00006	-0.00006
				(0.13)	(0.20)	(0.58)	(0.60)	(0.61)
SurpComp							-0.00755	-0.00647
							(6.34)***	(4.59)***
Rate_Hike				0.00726	-0.01396	0.00013	0.00073	0.00071
				(4.73)***	(2.95)***	(0.13)	(0.92)	(0.88)
Rate_Cut				-0.00124	-0.00719		-0.00069	-0.00023
				(0.77)	(5.84)***		(0.81)	(0.27)
Subprime				0.03773	-0.00092	-0.00136	0.00236	0.00225
				(6.58)***	(0.64)	(0.96)	(2.02)**	(1.92)*
Global				0.03262		0.02051	-0.00148	-0.00227
				(6.64)***		(5.17)***	(0.58)	(0.89)
Postcrisis				-0.01044	-0.00204	0.00342	-0.02654	-0.02733
				(3.51)***	(0.66)	(2.11)**	(6.64)***	(6.82)***
Depository				0.00049	-0.00106	-0.00059	-0.00042	-0.00042
				(0.27)	(0.76)	(1.07)	(1.04)	(1.05)
Non_Dep_CI				-0.00236	-0.00229	-0.00146	-0.00187	-0.00187
				(1.14)	(1.47)	(1.58)	(2.71)***	(2.71)***
BDES				0.00108	0.00255	-0.00003	0.00098	0.00098
				(0.56)	(1.64)	(0.05)	(2.02)**	(2.03)**
Insurance				0.00005	-0.00268	-0.00091	-0.00108	-0.00108
				(0.03)	(1.81)*	(1.57)	(2.64)***	(2.64)***
_cons	0.00977	-0.00162	-0.00038	0.00636	0.00709	-0.00094	0.00119	0.00114
	(3.37)***	(0.78)	(0.30)	(1.37)	(1.65)*	(0.42)	(0.62)	(0.60)
N	3,307	2,828	5,664	3,305	2,822	5,652	11,779	11,779

*Notes: The table presents the results from panel data regressions of the estimated CARs. The CARs are estimated using (-260, -5) estimation windows and (0, 0) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

Table A.6 – Results for CAR panel data regressions: 5-day event window

CAR(-1, +3)	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**-0.00005** (1.17)	**0.00018** (5.24)***	**-0.00005** (2.21)**	**-0.00009** (2.08)**	**0.00015** (4.15)***	**-0.00005** (2.36)**	**-0.00002** (1.14)	**-0.00002** (1.17)
Market_Cap				-0.00064 (0.84)	-0.00156 (2.93)***	0.00022 (0.58)	-0.00058 (2.02)**	-0.00058 (2.01)**
MtB				-0.00110 (2.91)***	-0.00055 (1.12)	-0.00035 (1.05)	-0.00067 (3.31)***	-0.00067 (3.32)***
SurpComp							-0.00175 (0.67)	0.00410 (1.51)
Rate_Hike				0.01569 (5.04)***	-0.02882 (3.06)***	-0.00327 (1.85)*	0.00538 (3.69)***	0.00524 (3.60)***
Rate_Cut				-0.01831 (5.62)***	-0.00395 (1.48)		-0.00918 (4.60)***	-0.00885 (4.51)***
Subprime				0.00391 (0.73)	0.00213 (0.69)	-0.00361 (1.59)	0.00363 (1.94)*	0.00386 (2.05)**
Global				0.01081 (1.55)		0.02570 (3.00)***	0.00460 (0.94)	0.00502 (1.02)
Postcrisis				-0.03616 (2.92)***	-0.02662 (4.52)***	0.01702 (5.01)***	-0.01389 (1.86)*	-0.01347 (1.81)*
Depository				-0.00143 (0.32)	0.00034 (0.23)	-0.00043 (0.36)	-0.00051 (0.37)	-0.00051 (0.37)
Non_Dep_CI				-0.00245 (0.50)	-0.00146 (0.49)	0.00042 (0.20)	-0.00081 (0.58)	-0.00081 (0.58)
BDES				-0.00105 (0.24)	0.00656 (2.93)***	0.00086 (0.72)	0.00184 (1.35)	0.00184 (1.35)
Insurance				-0.00702 (1.62)	0.00059 (0.36)	0.00169 (1.52)	-0.00097 (0.73)	-0.00097 (0.73)
_cons	0.00911 (1.89)*	0.04366 (9.45)***	-0.01474 (5.67)***	0.01802 (1.86)*	0.07099 (8.36)***	-0.01602 (3.64)***	0.01408 (4.10)***	0.01390 (4.05)***
N	3,307	2,828	5,664	3,305	2,822	5,652	11,779	11,779

*Notes: The table presents the results from panel data regressions of the estimated CARs. The CARs are estimated using (-260, -5) estimation windows and (-1, +3) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

Table A.7 – Results for CMAR panel data regressions: 3-day event window

CMAR(-1, +1)	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**-0.00004**	**0.00008**	**-0.00007**	**-0.00006**	**0.00006**	**-0.00004**	**-0.00003**	**-0.00003**
	(1.03)	(2.92)***	(4.64)***	(1.63)	(2.23)**	(2.90)***	(1.61)	(1.64)
Market_Cap				-0.00019	-0.00015	-0.00012	-0.00022	-0.00022
				(0.29)	(0.39)	(0.46)	(0.78)	(0.77)
MtB				-0.00033	0.00009	0.00046	0.00011	0.00011
				(0.98)	(0.28)	(2.31)**	(0.70)	(0.70)
SurpComp							-0.00477	-0.00104
							(1.96)**	(0.38)
Rate_Hike				0.00105	-0.06036	-0.00272	-0.00048	-0.00054
				(0.48)	(7.44)***	(2.05)**	(0.42)	(0.47)
Rate_Cut				-0.00580	-0.00632		-0.00195	-0.00154
				(2.42)**	(2.14)**		(1.42)	(1.13)
Subprime				0.00138	0.00345	-0.00883	0.00346	0.00352
				(0.35)	(1.17)	(4.32)***	(2.18)**	(2.21)**
Global				-0.02386			-0.01853	-0.01870
				(3.71)***			(3.68)***	(3.73)***
Postcrisis				-0.06333	-0.05135	0.01888	-0.02169	-0.02186
				(6.01)***	(8.66)***	(3.66)***	(3.20)***	(3.24)***
Depository				-0.00029	-0.00129	-0.00160	-0.00116	-0.00116
				(0.09)	(0.72)	(1.88)*	(1.01)	(1.01)
Non_Dep_CI				-0.00262	-0.00257	-0.00120	-0.00183	-0.00182
				(0.74)	(1.09)	(1.03)	(1.42)	(1.42)
BDES				0.00291	0.00446	-0.00070	0.00165	0.00165
				(0.85)	(2.15)**	(0.65)	(1.32)	(1.32)
Insurance				-0.00378	-0.00178	0.00103	-0.00099	-0.00099
				(1.20)	(1.01)	(1.09)	(0.93)	(0.93)
_cons	0.00948	0.03636	0.00076	0.01361	0.06621	0.00133	0.01658	0.01652
	(3.10)***	(10.68)***	(0.35)	(1.12)	(8.96)***	(0.26)	(3.25)***	(3.24)***
N	*3,417*	*2,875*	*5,746*	*3,412*	*2,863*	*5,729*	12,004	12,004

*Notes: The table presents the results from panel data regressions of the estimated CMARs. The CMARs are estimated over (-1, +1) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

Table A.8 - Results for CMAR panel data regressions: 1-day event window

CMAR(0, 0)	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**0.00003**	**0.00010**	**0.00000**	**0.00003**	**0.00010**	**0.00000**	**0.00003**	**0.00002**
	(1.27)	(5.42)***	(0.41)	(1.22)	(5.37)***	(0.15)	(2.35)**	(2.32)**
Market_Cap				-0.00114	-0.00047	-0.00027	-0.00059	-0.00059
				(2.43)**	(1.70)*	(1.50)	(3.19)***	(3.19)***
MtB				0.00004	0.00025	-0.00005	0.00002	0.00002
				(0.13)	(1.47)	(0.38)	(0.24)	(0.24)
SurpComp							-0.00493	-0.00332
							(3.79)***	(1.97)**
Rate_Hike				0.00678	-0.02166	0.00032	0.00069	0.00067
				(4.29)***	(4.64)***	(0.31)	(0.91)	(0.87)
Rate_Cut				0.00428	-0.00939		0.00315	0.00349
				(2.33)**	(5.43)***		(3.23)***	(3.50)***
Subprime				0.00461	-0.00147	-0.00151	0.00109	0.00106
				(1.64)	(1.03)	(1.02)	(0.87)	(0.83)
Global				-0.00697			-0.00823	-0.00865
				(1.90)*			(2.98)***	(3.07)***
Postcrisis				-0.05568	-0.00905	-0.02649	-0.03990	-0.04032
				(9.27)***	(2.95)***	(7.20)***	(8.77)***	(8.79)***
Depository				0.00084	-0.00107	-0.00078	-0.00042	-0.00042
				(0.40)	(0.74)	(1.21)	(0.57)	(0.57)
Non_Dep_CI				-0.00304	-0.00250	-0.00180	-0.00224	-0.00224
				(1.22)	(1.50)	(2.14)**	(2.54)**	(2.54)**
BDES				0.00355	0.00122	0.00039	0.00157	0.00157
				(1.56)	(0.79)	(0.53)	(1.93)*	(1.93)*
Insurance				-0.00034	-0.00298	-0.00125	-0.00146	-0.00146
				(0.16)	(1.92)*	(1.80)*	(1.94)*	(1.94)*
_cons	0.00695	-0.00031	0.00174	0.02169	0.01753	0.00694	0.01253	0.01249
	(3.27)***	(0.15)	(1.39)	(2.63)***	(3.10)***	(2.21)**	(3.93)***	(3.92)***
N	3,417	2,875	5,746	3,412	2,863	5,729	12,004	12,004

*Notes: The table presents the results from panel data regressions of the estimated CMARs. The CMARs are estimated over (0, 0) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

Table A.9 – Results for CMAR panel data regressions: 5-day event window

CMAR(-1, +3)	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Negative Surprise*	*Positive Surprise*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**0.00001**	**0.00012**	**-0.00004**	**-0.00002**	**0.00010**	**-0.00003**	**0.00000**	**0.00000**
	(0.20)	(3.83)***	(1.89)*	(0.48)	(2.98)***	(1.14)	(0.04)	(0.02)
Market_Cap				-0.00126	-0.00160	-0.00008	-0.00092	-0.00092
				(1.53)	(2.96)***	(0.21)	(2.75)***	(2.76)***
MtB				-0.00052	0.00003	0.00021	-0.00010	-0.00010
				(1.29)	(0.06)	(0.93)	(0.55)	(0.55)
SurpComp							-0.00020	0.00567
							(0.08)	(2.19)**
Rate_Hike				0.01554	-0.03353	-0.00216	0.00507	0.00498
				(5.34)***	(3.54)***	(1.23)	(3.55)***	(3.47)***
Rate_Cut				-0.00790	-0.00375		-0.00233	-0.00209
				(2.31)**	(1.12)		(1.18)	(1.06)
Subprime				0.00308	-0.00092	-0.00441	-0.00183	-0.00157
				(0.63)	(0.29)	(1.99)**	(0.88)	(0.76)
Global				0.01742		-0.01048	0.00783	0.00843
				(2.57)**		(1.26)	(1.63)	(1.73)*
Postcrisis				-0.06481	-0.05539	0.00811	-0.00817	-0.00756
				(5.55)***	(7.32)***	(2.25)**	(1.20)	(1.11)
Depository				-0.00151	0.00073	-0.00143	-0.00095	-0.00094
				(0.43)	(0.45)	(1.02)	(0.65)	(0.64)
Non_Dep_CI				-0.00517	-0.00179	-0.00083	-0.00232	-0.00232
				(1.25)	(0.54)	(0.41)	(1.42)	(1.42)
BDES				0.00026	0.00826	0.00059	0.00239	0.00240
				(0.08)	(3.75)***	(0.40)	(1.61)	(1.61)
Insurance				-0.00573	0.00134	0.00168	-0.00051	-0.00050
				(1.68)*	(0.78)	(1.20)	(0.36)	(0.36)
_cons	0.00668	0.05149	-0.00437	0.02384	0.08984	-0.00394	0.02760	0.02753
	(1.68)*	(11.39)***	(1.50)	(1.71)*	(7.93)***	(0.57)	(4.82)***	(4.80)***
N	3,417	2,875	5,746	3,412	2,863	5,729	12,004	12,004

*Notes: The table presents the results from panel data regressions of the estimated CMARs. The CMARs are estimated over (-1, +3) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorized at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01.*

Table A.10 - Controlling for the zero-lower-bound (ZLB) period

	CAR(1, 1)	*CMAR(1, 1)*
SRISK	**-0.00009**	**-0.00007**
	(4.04)***	(2.82)***
SRISK_flat_yc	**0.00007**	**0.00007**
	(2.19)**	(2.08)**
SRISK_PS	**0.00014**	**0.00008**
	(4.57)***	(2.58)***
SurpComp	0.00780	0.00693
	(1.97)**	(1.71)*
SurpComp_flat_yc	-0.01732	-0.01228
	(2.89)***	(1.93)*
SurpComp_ZLB	0.16145	0.11618
	(6.53)***	(4.86)***
Term_Spread	0.00178	0.00105
	(2.00)**	(1.25)
Flat_yc	-0.00072	-0.00157
	(0.50)	(1.06)
Market_Cap	0.00013	-0.00017
	(0.56)	(0.59)
MtB	-0.00026	0.00014
	(1.71)*	(0.93)
Rate_Hike	0.00040	-0.00233
	(0.32)	(1.75)*
Rate_Cut	-0.00694	-0.00298
	(4.45)***	(1.83)*
Subprime	0.00382	0.00269
	(2.20)**	(1.58)
Global	-0.01559	-0.01815
	(2.79)***	(3.39)***
Postcrisis	-0.02218	-0.02233
	(2.80)***	(3.07)***
ZLB	**-0.00693**	**-0.01175**
	(2.83)***	(4.51)***
Depository	-0.00093	-0.00110
	(0.87)	(0.97)
Non_Dep_CI	-0.00118	-0.00199
	(1.03)	(1.50)
BDES	-0.00001	0.00148
	(0.01)	(1.20)
Insurance	-0.00157	-0.00097
	(1.52)	(0.91)
_cons	0.01337	0.01810
	(4.60)***	(3.66)***
N	11,779	12,004

*Notes: The table presents the results from running the same regressions as in **Table 8** while also controlling for the ZLB period. The variable ZLB is a dummy which is equal to 1 for the period when the lower bound of the FOMC target rates reached zero, namely from 16/12/2008 to 28/10/2015, and zero otherwise. SurpComp_ZLB is an interaction term between the unexpected component of the announced target rates and the ZLB period. The remaining variables are the same as what is described in the explanations for Table 8. * p<0.1; ** p<0.05; *** p<0.01*

Table A.11 - Panel data regressions of CARs estimated using a Fama-French-Carhart model

CAR(-1, +1)	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*	*Negative Surprises*	*Positive Surprises*	*Zero Surprise*	*Whole sample*	*Whole sample*
SRISK	**-0.00013**	**0.00006**	**-0.00005**	**-0.00014**	**0.00006**	**-0.00004**	**-0.00005**	**-0.00005**
	(2.72)***	(1.79)*	(3.21)***	(3.09)***	(1.69)*	(2.75)***	(2.73)***	(2.74)***
SurpComp							0.00358	0.00700
							(1.59)	(2.94)***
Rate_Hike				0.00264	-0.03514	-0.00198	0.00076	0.00068
				(0.94)	(3.81)***	(1.41)	(0.61)	(0.55)
Rate_Cut				-0.01145	-0.00238		-0.00672	-0.00679
				(4.80)***	(1.21)		(4.74)***	(4.71)***
Subprime				-0.01990	0.00056	-0.00440	0.00493	0.00515
				(1.96)**	(0.20)	(2.10)**	(2.84)***	(2.96)***
Global				-0.01255			0.00973	0.01053
				(1.38)			(1.95)*	(2.12)**
Postcrisis				-0.00724	-0.02755	-0.01197	0.00154	0.00234
				(1.30)	(3.98)***	(2.18)**	(0.21)	(0.32)
Depository				0.00161	-0.00091	-0.00097	-0.00020	-0.00020
				(0.38)	(0.54)	(1.12)	(0.21)	(0.21)
Non_Dep_CI				-0.00281	-0.00169	-0.00048	-0.00141	-0.00141
				(0.62)	(0.66)	(0.41)	(1.46)	(1.46)
BDES				0.00058	-0.00045	-0.00180	-0.00073	-0.00073
				(0.14)	(0.21)	(1.58)	(0.70)	(0.70)
Insurance				-0.00123	-0.00200	0.00097	-0.00027	-0.00027
				(0.30)	(1.15)	(1.08)	(0.29)	(0.29)
_cons	0.00902	0.02218	-0.00103	0.00811	0.03835	-0.00056	0.00792	0.00783
	(2.04)**	(5.47)***	(0.43)	(1.42)	(5.90)***	(0.23)	(3.52)***	(3.49)***
N	3,091	2,610	5,366	3,091	2,610	5,366	11,067	11,067

*Notes: The table presents the results from panel data regressions of the estimated CARs. The CARs are estimated using a 4-factor Fama-French-Carhart model over (-260, -5) estimation windows and (-1, +1) event windows. The first three columns run the regressions with no controls while the remaining columns show the results for regressions including controls. Unlike the cases for the CARs estimated via a market model, the control variables do not include market cap and market-to-book ratio in these regressions as the 4-factor model already accounts for these factors. Columns labelled 'Positive surprise' ('Negative surprise') refer to the subsample of the events on which the FOMC target rate announcement was higher (lower) than the expected rate. 'Zero surprise' limits the sample only to the announcements that were fully anticipated by the market. The last two columns control for the surprise component rather than splitting the sample based on the sign of the surprise component. In the eighth column, SurpComp is winsorised at 1% and 99% levels similar to all other variables in all the cases. All estimations are run using random effects models controlling for year fixed effects. Standard errors are clustered at firm level. The numbers in parentheses represent the Z statistics. * p<0.1; ** p<0.05; *** p<0.01*

STUDY II:

Systemic Risk, Liquidity Creation and Market Discipline

Abstract

We employ a Bayesian panel Vector Autoregression (VAR) model to study the bidirectional dynamics between bank liquidity creation and bank systemic risk. We find evidence that liabilities-side liquidity creation activities, which can improve market discipline, tend to reduce systemic risk in the long-run. On the other hand, assets-side and off-balance sheet liquidity creation tend to increase it. Finally, we document that shocks to systemic risk lead to significant rises in the bank's liquidity creation activities, especially for liabilities-side liquidity creation. These findings are consistent with recent theories suggesting that exposure to the threat of bank runs and fire sales relaxes borrowing conditions for banks.

Keywords: liquidity creation, systemic risk, market discipline, financial sector, Bayesian VAR

1. Introduction

Liquidity creation is key to the functioning of a modern economy. By using liquid liabilities (e.g. customer deposits) to purchase illiquid assets (e.g. corporate loans), banks provide liquidity to firms and households, providing essential support to the real economy. Consistent with this view, there is evidence that bank liquidity creation is positively associated with real economic output (Berger and Sedunov 2017) and is important for the monetary policy transmission mechanism (Kishan and Opiela 2000).

However, an excessively high volume of liquidity creation can also pose a threat to financial stability. For example, Berger and Bouwman (2017) show that high levels of bank liquidity creation in the economy are associated with a higher likelihood of a crisis. Bats and Houben (2020) show that country-level systemic risk is higher when bank financing dominates financial market financing, suggesting that bank liquidity creation might be beneficial to the real economy only under certain conditions, and up to a certain limit. Fungacova, Turk, and Weill (2015) show that a rise in liquidity creation activities increases the probability of bank failures. Finally, Roberts, Sarkar, and Shachar (2018) report that the banks that create less liquidity due to Liquidity Coverage Ratio requirements tend to be more resilient to fire-sale risk, although this comes at the price of reduced lending.

In this paper, we investigate the interlinkages between bank systemic risk and liquidity creation, as well as the different components of liquidity creation, to understand the potential mechanisms underlying these relationships. This issue is important for several reasons. First, understanding the effect of a bank's core activities (i.e., liquidity creation) on its systemic risk is key to implementing effective and efficient policies to contain systemic risk. Second, identifying the causal relationship between various types of liquidity creation and systemic risk can help us with the assessment of the current macroprudential policies and regulations in place (i.e., whether the policies are targeting the true source of systemic risk). Third, from the investors' point of view, understanding this relationship can have important implication for risk and portfolio management. Finally, the consequences of bank systemic risk for liquidity creation can help us better understand the behaviour of bank managers, and whether they have incentives to deliberately inflate systemic risk to benefit from lower borrowing restrictions.

Understanding the relationship between bank systemic risk and liquidity creation becomes more crucial when analysing the consequences of policy interventions at times of crisis. A financial crisis is typically characterised by extreme levels of systemic risk and a drop in liquidity provision by financial institutions. Therefore, the aim of authorities under such circumstances is to reduce systemic risk while facilitating the provision of liquidity to the economy. Such an optimal outcome, however, is not always easy to achieve. Berger et al. (2016) examine the effects of regulatory interventions and capital support on bank liquidity creation and risk-taking in Germany. They find that both policy actions reduce bank risk taking, however regulatory interventions also reduce liquidity creation, while capital support does not have an impact of liquidity creation. Similarly, Bowe, Kolokolova, and Michalski (2017) show that various policy responses by the US authorities to the 2007-2009 financial crisis, such as the quantitative easing and the Troubles Asset Relief Program (TARP), have generally had a negative impact on bank liquidity creation.

However, because of the complexity of circumstances during the crisis, the findings on the effects of government interventions such as TARP on bank liquidity creation (or lending) and bank risk-taking are mixed and inconclusive (Black and Hazelwood 2013; Kiser, Prager, and Scott 2012; Li 2013). The emerged intricacies of designing and implementing appropriate bailout regimes such as TARP to secure financial stability led to important post crisis regulatory changes. One such change is the Orderly Liquidation Authority (Title II of the Dodd-Frank act), which provides a framework for fast and efficient liquidation of large financial institutions which are on the verge of failing.

A distinctive aspect of this study's approach is the consideration of potential feedback effects between systemic risk and liquidity creation. Previous studies that investigate the effects of liquidity creation on systemic risk predominantly regard liquidity creation as exogenous (e.g. Berger and Bouwman 2017; Fungacova, Turk, and Weill 2015). However, higher exposure to fire sales and systemic distress can improve market discipline and therefore relax borrowing constraints for the bank

(Morrison and Walther 2020).[1] Motivated by this potential feedback effect, we employ Bayesian panel vector autoregression (VAR) models to study the bilateral interactions between bank systemic risk and liquidity creation. To the best of our knowledge, we are the first study to investigate this dynamic relationship at bank level in a panel VAR framework. Importantly, this approach allows us to estimate the duration and time-varying impact of shocks in the endogenous variables in the model.

Our findings provide evidence that shocks to total liquidity creation lead to a significant increase in systemic risk in the upcoming quarters. This contrasts with the recent findings by Davydov, Vähämaa, and Yasar (2021), who show that bank liquidity creation and all its components are negatively associated with systemic risk. According to our results, the positive response of systemic risk tends to be the strongest in the 3rd quarter following the shock. This is plausibly the duration it takes until the negative consequences of low-quality illiquid loans start to become prominent.

The positive effect of liquidity creation on systemic risk is mainly driven by off-balance sheet and assets-side liquidity creation. Among all the components, shocks to off-balance sheet liquidity creation have the strongest effect on systemic risk, causing significant rises that last for as long as five years, potentially due to long-term commitments made via off-balance sheet guarantees. On the contrary, liabilities-side liquidity creation has a significantly negative effect on systemic risk in the long-run. This negative effect seems to outweigh the positive effect of assets-side liquidity creation causing the aggregate effect of on-balance sheet liquidity creation to be negative too. Therefore, similar to Davydov, Vähämaa, and Yasar (2021), our results show that shocks to on-balance sheet liquidity creation tend to significantly reduce systemic risk after almost a year following the shock.

These findings are important because the existing literature on the effects of the different components of bank liquidity creation on the banking system and the real economy provides mixed findings. For instance, several studies suggest that off-balance sheet banking activities enhance market

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[1] Morrison and Walther (2020) argue that this effect can give banks the incentive to make correlated asset choices even in the absence of regulatory advantages of being systemically important.

discipline and reduce bank risk (Angbazo 1997; Boot and Thakor 1991; Hassan 1993; Hassan, Karels, and Peterson 1994). However, Berger and Bouwman (2017) show that the increase in the likelihood of a financial crisis that results from high liquidity creation is mainly driven by off-balance sheet liquidity creation. Our results contribute to this literature by providing new evidence suggesting a positive effect of off-balance sheet liquidity creation and negative effect of on-balance sheet liquidity creation on bank systemic risk.

The second important contribution of this paper is that it uncovers a potential benefit of liabilities-side liquidity creation which has so far been neglected by the literature: market discipline. This is in line with the view that higher bank leverage and uninsured deposit financing can encourage bank managers to reduce the threat of bank runs (Calomiris and Kahn 1991).

The third contribution of our paper is the quantification of the impact of systemic risk on liquidity creation. Our results show that shocks to systemic risk lead to significant rises in bank liquidity creation in the following quarters. This effect is observed for all components of bank liquidity creation, although liabilities-side liquidity creation tends to exhibit the strongest response. Hence, once again, our study highlights the importance of the relationship between liabilities-side liquidity creation and systemic risk, in both directions. In particular, we add to the existing literature by providing empirical evidence in support of a theoretical model proposed by Morrison and Walther (2020) regarding the impact of systemic risk on market discipline. Our findings suggest that banks have incentives to deliberately inflate their levels of systemic risk to ease their borrowing conditions and create more liquidity.

Our findings have important implications in financial regulation and policy. Although market discipline is usually regarded as a tool of micro-prudential regulation (Acharya and Thakor 2016), we find evidence that market discipline can reduce bank systemic risk, and thus it might also have macro-economic implications. Therefore, policy measures that restrict banks' off-balance sheet and assets-side activities are likely to be more effective in tackling financial system fragility. Moreover, the positive impact of systemic risk on liquidity creation implies that policy measures that constrain bank systemic risk come at the expense of financial intermediation activity. Previous studies also report banks that undergo stress tests or are subject to regulatory interventions (which aim to reduce bank risk-taking) tend to reduce liquidity creation activities over the following periods (Berger et al. 2016, 2010; Nguyen et al. 2020). This paper, however, highlights a channel that so far has been neglected: the impact of systemic risk on borrowing conditions for banks.

The remainder of this paper is organised as follows. Section **2** provides a review of the previous studies and our proposed hypotheses. Section **3** provides detailed information about our sample banks, variables and econometric methodology. Section **4** presents and discusses the results. Section **6** concludes.

2. Literature review and hypothesis development

The positive impact of liquidity creation and its different components on the real economy has been documented in previous studies (Berger and Sedunov 2017). Bank loans and different forms of credit supply contribute to economic output and aggregate demand through the bank lending channel (Bernanke and Blinder 1988). Nevertheless, an excessive volume of bank liquidity creation can adversely affect financial stability, arguably through two main channels.

The first channel is a reduction in lending standards, which tends to occur due to an increased flow of deposits into the banking system when macroeconomic risk is high (Acharya and Naqvi 2012; Dell'Ariccia, Igan, and Laeven 2012; Keys et al. 2010). When macroeconomic risk is high, investors seeking safer assets rebalance their portfolios by investing more in bank deposits (which are considered a safe asset). Banks respond to such an inflow of funds by relaxing lending standards to be able to increase their lending volumes (Acharya and Naqvi 2012), leading to higher liquidity creation. Moreover, credit booms due to lax lending policies can be exacerbated by securitisation activities (Acharya and Naqvi 2012; Dell'Ariccia, Igan, and Laeven 2012; Keys et al. 2010). The second possible channel is leverage, which is found to be a major contributor to financial system fragility (Acharya and Thakor 2016; Allen and Gale 2008; Goel, Song, and Thakor 2014).

However, within this framework, predicting the net effect of liquidity creation on systemic risk is difficult firstly because of the contradictory effects leverage can have on systemic risk. While a higher leverage can increase the risk of bank default, it might also increase debtholder discipline (Acharya and Thakor 2016), especially from debtholders with sophisticated monitoring technologies and low monitoring costs (Birchler 2000). Several studies have documented that deposit guarantees, which can lessen market discipline, may result in higher banking fragility (Demirgüç-Kunt and Detragiache 1998, 2002; Demirgüç-Kunt and Huizinga 2004). Similarly, changes in the debt priority ladder that shift monitoring incentives to debtholders with lower monitoring costs and better monitoring technologies can reduce bank risk taking (Danisewicz et al. 2018). Therefore, if a rise in liquidity creation is due to an increase in bank debt where the debtholder has monitoring possibilities, it might lead to a reduction in bank systemic risk.

In addition to the market discipline effect, there are other channels through which liquidity creation can be positively related to bank stability. First, since liquidity creation is considered as the core of banking activity, a low liquidity creation can be a signal of poor functioning of a bank (Fungacova, Turk, and Weill 2015) and subsequently higher distress risk. Second, previous evidence shows that (smaller) banks tend to strengthen their solvency standards when facing a high liquidity risk (Distinguin, Roulet, and Tarazi 2013). Therefore, a higher liquidity creation can urge banks to strengthen their capital buffers and reduce risk exposure.

Based on the two contradictory potential effects of liquidity creation on systemic risk discussed above, we develop the following testable hypotheses:

Leverage and lending risk hypothesis: an increased level of bank liquidity creation leads to higher systemic risk as higher liquidity creation is associated with higher leverage and low lending standards.

However, as discussed above, increased liquidity creation can also lead to a lower distress risk via the explained channels. The findings of Chatterjee (2018), Zheng and Cronje (2019) and Davydov, Vähämaa, and Yasar (2021) support this view as they discover a negative relationship between liquidity creation and bank fragility. Therefore, our alternative hypothesis is as follows:

Market discipline hypothesis: an increased level of bank liquidity creation leads to reductions in systemic risk as higher liquidity creation can be associated with higher market discipline and stricter risk management by bank managers.

However, as explained earlier, the relationship between liquidity creation and systemic risk is very likely to be bidirectional. Morrison and Walther (2020) present a general equilibrium model where banks rationally choose to make investments correlated with the aggregate market to be exposed to a higher threat of bank runs and fire sales in the event of a crisis. This means the bank would be more severely punished for bad asset choices and therefore it implies a stricter market discipline from the lenders' perspective. Thus, banks have incentives to intentionally inflate their systemic risk in order to benefit from more relaxed borrowing conditions, which come in tandem with higher market discipline. In turn, the relaxed borrowing conditions can lead to a higher level of liquidity creation. Diamond and Rajan (2001) also explain how financial fragility (induced by depositors' threat of bank runs) facilitates liquidity creation by banks where specialised knowledge is required to collect loan repayments (i.e., loans are highly illiquid). Motivated by this potential feedback effect, we empirically test the following hypothesis:

Relaxed borrowing conditions hypothesis: an increase in bank systemic risk leads to higher levels of liquidity creation, as higher systemic risk implies a stricter market discipline and more relaxed borrowing conditions.

On the other hand, an increased level of systemic risk can make a bank subject to stricter macroprudential regulations and cause a reduction in the bank's liquidity creation. Existing evidence shows that banks tend to restrict their lending and liquidity creation activities due to stress tests being conducted on them (Acharya, Berger, and Roman 2018; Berrospide and Edge 2019; Bordo and Duca 2018). Supervisory assessments and stress tests such as the Comprehensive Capital Analysis and

Review (CCAR), the Dodd-Frank Act Stress Testing (DFAST) and the Supervisory Capital Assessment Program (SCAP) impose strict capital requirements on banks that fail to meet the financial robustness standards, hence encouraging them to adjust their balance sheets towards safer and more liquid assets. Based on this argument, we propose the following as an alternative to the "relaxed borrowing conditions" hypothesis:

Prudential balance sheet adjustment hypothesis: an increase in bank systemic risk results in a reduction in the bank's liquidity creation activities, due to precautionary measures taken by the bank managers to avoid facing tighter regulatory requirements.

We run tests in remainder of this paper to empirically test the abovementioned hypothesis using a panel data VAR framework. The details about our analysed liquidity creation and systemic risk measures as well as our methodology are elaborated in the following section.

3. Data and Methodology

We study the dynamics between bank systemic risk and liquidity creation using quarterly data for a sample of 111 US banks for the period from January 2000 to December 2016. Our preferred systemic risk measure is the SRISK index introduced by Acharya, Engle, and Richardson (2012). This measure is fundamentally based on the marginal expected shortfall (MES) of a bank, and adopts a similar approach to the systemic expected shortfall (SES) measure, introduced by Acharya et al. (2017). In the following subsections we provide further details on SRISK index including the estimation process.

We study the five main liquidity creation measures introduced in the seminal work by Berger and Bouwman (2009). First, we study the relationship between a bank's total liquidity creation and its systemic risk. In the next stage we break down total liquidity creation into on-balance sheet and off-balance sheet liquidity creation and run tests with each separately. Lastly, we run our model individually with each of the two components of on-balance sheet liquidity creation, namely assets-side and liabilities-side liquidity creation.

We carry out our analysis in a Bayesian panel VAR framework. VAR models are particularly appropriate for our research questions since the previous theoretical studies (e.g. Acharya and Thakor 2016; Morrison and Walther 2020) propose an interrelated nexus between liquidity creation and systemic risk. In the next subsections, we first explain the estimation process for SRISK, next we provide details on our liquidity creation measures. Finally, we elaborate on our Bayesian panel VAR model used for estimation.

3.1. Measuring systemic risk

Systemic risk has been a central topic in the context of financial stability and macroprudential regulation particularly since the financial crisis of 2007-2009. Several papers so far have attempted to introduce a quantifiable and easy to implement measure to evaluate bank systemic risk. One of the broadly cited works in this regard is the paper by Acharya et al. (2017). In this paper, a measure of systemic risk called Systemic Expected Shortfall (SES) is introduced which is based on a firm's leverage and marginal expected shortfall (MES). In simple terms, SES measures the propensity of a firm being undercapitalised when the system as a whole is undercapitalised. Using mathematical notation, SES can be presented as follows:

$$SES^i \equiv E\left[\tau a^i - \omega^i \,\middle|\, W < \tau A\right] \tag{1}$$

The formula calculates how much the equity value of firm i, denoted by ω^i is expected to go below a required threshold, which is defined as the fraction τ of the firm's total assets a^i, in case the equity capital in the aggregate banking system, W, drops below τ faction of the system's total assets, A. Acharya et al. (2017) conclude from their introduced model that SES can be regarded as a system-wide externality of financial institutions' risk-taking activities hence taxing the institutions based on their SES level can improve financial system stability.

In another seminal work in this area Acharya, Engle, and Richardson (2012) develop the theoretical model presented in Acharya et al. (2017)[2] to introduce a novel systemic risk measure called SRISK. SRISK adopts a similar approach to SES and depends on size, leverage and the time-varying correlation between the firm's stock return and the market return. The Volatility Institute of NYU Stern School of Business provides data and descriptions on the estimation process of SRISK. We follow the same steps as explained on V-Lab's website to estimate SRISK for our sample banks[3]. The SRISK value of a bank represents the bank's expected capital shortfall in case a crisis happens. This can be expressed as:

$$SRISK_{i,t} = E_{t-1}(Capital\ Shortfall_i\ |Crisis) \tag{2}$$

The key point here is how we define "capital shortfall" and "crisis". SRISK is computed based on a pre-defined prudential capital ratio which is typically set as 8%. Based on this prudential capital ratio, which we will denote by *k,* the above formula can be further expanded as:

$$SRISK_{i,t} = E\big((k(Debt + Equity) - Equity)\ |\ Crisis\big) \tag{3}$$

Therefore, similar to SES, SRISK shows us how much the equity value of the firm is expected to go below *k%* of its total assets, conditional on a crisis breaking out. Applying the crisis condition on our expected value requires us to define the Long-run Marginal Expected Shortfall (LRMES) of the bank. LRMES measures the fractional loss of the bank's equity value conditional on a significant drop in the aggregate market in a six-month horizon, and can be calculated as:

$$LRMES_{i,t} = 1 - \exp(\log(1-d) \times \beta_{i,t}) \tag{4}$$

Where d is the assumed six-month crisis threshold for the market (40% by default) and β is the market beta of the firm which is estimated using a combination of the constant and time-varying betas. More specifically the "nested beta" is estimated using the following equation:

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[2] This paper was initially released in 2010 as a working paper.

[3] Additional details on the estimation of SRISK can be found on V-Lab's website: https://vlab.stern.nyu.edu.

$$r_{i,t} = (\emptyset_1 + \emptyset_2 \beta_{i,t}) r_{m,t} + \sqrt{h_{i,t}} \xi_{i,t} \tag{5}$$

Where $r_{i,t}$ and $r_{m,t}$ are the firm and the market returns, $\beta_{i,t}$ is the time-varying beta and $(\emptyset_1 + \emptyset_2 \beta_{i,t})$ is the nested beta which combines the time-varying and constant betas. This approach allows our model to reduce noise and have more consistent estimations for the covariances. The error terms are assumed to be a GJR-GARCH(1, 1) with the conditional heteroscedasticity $h_{i,t}$ and the innovation term $\xi_{i,t}$.

Therefore, having computed LRMES, the SRISK equation can be expanded as:

$$\begin{aligned} SRISK_{i,t} &= E\left(\left(k\left(Debt_{i,t} + Equity_{i,t}\right) - Equity_{i,t}\right) \mid Crisis\right) \\ &= kDebt_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right) \times Equity_{i,t} \end{aligned} \tag{6}$$

We use SRISK in our analysis mainly because it is a comprehensive measure that takes into account the volatility of the stock returns as well as the correlation between the stock and the market. This is the main advantage of this measure to other similar measures such as CoVaR proposed by Adrian and Brunnermeier (2016). Although CoVaR also captures the tail dependency between the bank and the financial system, it is not affected by the bank's stock return volatility (Acharya, Engle, and Richardson 2012). Nevertheless, there is empirical evidence that suggests both SRISK and CoVaR approaches lead to similar systemic risk rankings for the financial institutions (Lin, Sun, and Yu 2018).

3.2. Measuring bank liquidity creation

Although bank liquidity creation has been studied extensively for a long time, the recent empirical literature has predominantly employed the measurements introduced by Berger and Bouwman (2009). By categorising a bank's on-balance sheet and off-balance sheet activities into three classes of liquid, semi-liquid and illiquid, Berger and Bouwman (2009) introduce multiple measures of bank liquidity creation. **Table A.1** in Appendix **1** provides an overview of how this categorisation is done. On the assets side, various types of loans such as commercial, agricultural, and real estate loans as well as other holdings such as intangible assets are considered to be illiquid assets. Cash, securities, and trading assets on the other hand are classified as liquid assets. Similarly, on the liabilities side, deposits, in general, are assumed to be liquid liabilities whereas other types of liabilities, as well as equity, are categorised as illiquid. Lastly, off-balance sheet liquidity provision occurs when banks provide various off-balance sheet guarantees to the customers (e.g. letters of credit) to provide them with liquidity when and if necessary.

A bank generates liquidity by turning liquid liabilities into illiquid assets. For instance, the more customer deposits the bank takes and the more commercial loans the bank issues the higher the liquidity creation by the bank. Therefore, the weights are assigned to each of the described activities according to the bottom panel in **Table A.1**. Based on these criteria, 5 different liquidity creation measures are introduced, which we use in our analysis as well. The first measure is the total liquidity creation, which is typically referred to as "*catfat*". This is the preferred measure of Berger and Bouwman (2009) which includes both on-balance sheet and off-balance sheet activities. In the next stage, we look at the two components of *catfat* separately to investigate the individual dynamics of on-balance sheet liquidity creation (*catnonfat*) and off-balance sheet liquidity creation (*LC_OBS)* with systemic risk. Finally, we break down on-balance sheet liquidity creation into assets-side (*LC_A)* and liabilities-side (*LC_L*) liquidly creation and run tests on each measure separately. This enables us to distinguish more thoroughly between what we describe as the market-discipline-enhancing and the risk-generating consequences of liquidity creation. This is because liabilities-side liquidity creation is likely to play a more significant role for market discipline.

We collect all our data for the five liquidity creation measures from Christa Bouwman's website.[4] The next section elaborates on the econometric methodology we employ to analyse our variables of interest.

[4] https://sites.google.com/a/tamu.edu/bouwman/data

3.3. Econometric methodology

Vector autoregression (VAR) models are among popular econometric techniques used to analyse the dynamics between economic and financial time series. An important feature of VAR models, which makes them highly suitable for our research questions, is that all variables are treated as endogenous in a VAR framework. This is particularly important in our study since our arguments suggest a two-way and dynamic relation between bank systemic risk and liquidity creation. Therefore, classic linear regression models would prove insufficient to address our research questions.

Although VAR models are mainly applied to time-series data, there are available applications on panel data as well. Specific classes of panel VAR models are designed to capture different levels of interactions between different units of the panel data. Four specific panel data properties can potentially be explained by a panel VAR model: 1) Cross-sectional heterogeneity 2) Dynamic interdependencies 3) Static interdependencies 4) Dynamic heterogeneity. For instance, the random effect model allows for cross-sectional heterogeneity between the units, therefore the VAR coefficients and residuals are unit specific. In more complex applications, Canova and Ciccarelli (2009) and Canova and Ciccarelli (2013) propose models for Bayesian panel VAR estimations that allow for dynamic and static interdependencies between the units. ‘Static interdependencies’ implies that the residuals are allowed to be correlated across units, ‘dynamic interdependencies’ means that the dynamic behaviour of each unit is explained by its own lagged values as well as lagged values of other units. And finally, the Dynamic Structural Factor models (Canova and Ciccarelli 2013; Ciccarelli, Ortega, and Valderrama 2012) allow the VAR coefficients and the residuals variance-covariance matrix to be time-varying.

In all the described applications, the approach is to explain the behaviour of each unit separately by allowing different levels of interdependencies within the units. Our research purpose, however, is not to study the dynamics of systemic risk and liquidity creation individually for each bank. Therefore, to estimate our VAR models, we employ a Bayesian pooled estimator, which essentially relaxes all the properties discussed above. We discuss the details of the Bayesian estimation procedure in the following sections.

3.3.1. Basic properties of the panel VAR model

We set up our VAR model with 7 variables in total. We include 4 endogenous variables in our model: systemic risk (*SRISK)* and liquidity creation which are our variables of interest and risk-adjusted tier 1 capital ratio (*CAPR1)* and market capitalisation (*cap*) which we include as controls. Systemic risk and liquidity creation are measured as explained in sections **3.1** and **3.2**. We include risk-adjusted tier 1 capital ratio in our model since capital requirements are deemed fundamental for financial stability (Acharya and Thakor 2016), as suggested by Basel II requirements as well. Furthermore, Zheng and Cronje (2019) document a moderating effect of bank capital in the relationship between bank liquidity creation and bank failure risk. We also control for market capitalisation to ensure that the possible effects of systemic risk and liquidity creation are not due to the bank's size.

The data regarding risk-adjusted tier 1 capital ratio and market capitalisation are collected from CRSP-COMPUSTAT data sources. In a similar approach to Berger and Bouwman (2017), we detrend all our endogenous variables to meet the stationarity requirements for the VAR estimation. The calculated roots of our models' characteristic polynomials indicate that without detrending some roots lie outside the unit circle, hence the VAR model does not satisfy the stability condition without detrending the variables. However, the model is stable when variables are used in levels (and not in differences), therefore we do not difference (or standardise) the variables for the sake of simpler interpretation. We also winsorise the variables at 1% and 99% levels to minimise the effect of outliers.

In addition to the four endogenous variables described above, we include three exogenous variables in our system of equations as well. We include these variables to control for the macrostate of the economy and since they are macroeconomic data they are regarded as exogenous in our model. Berger and Bouwman (2017) find that monetary policy significantly affects liquidity creation by small banks. Therefore, one of our exogenous controls is the slope of the yield curve (*termspread)* measured by the spread between the 10-year and 3-month US Treasury bills. We also include industrial production growth (*indpro)* in our VAR model as a proxy for the business cycle, in a similar approach to Bekaert, Hoerova, and Duca (2013). Our third exogenous variable is a dummy controlling for the 2007-2009 crisis period (*crisis*), when the market conditions were extraordinary and important policy actions like the Quantitative Easing (QE) took place. Same as the endogenous variables, we also winsorise the exogenous variables at 1% and 99% levels.

We introduce four lags on the endogenous variables similar to Berger and Bouwman (2017). Ignoring the constant term, our panel VAR model can be represented as follows using a generic matrix notation:

$$Y = XB + \mathcal{E} \tag{7}$$

or:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_T \end{bmatrix}_{NT\times n} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_T \end{bmatrix}_{NT\times(np+m)} B_{(np+m)\times n} + \begin{bmatrix} \mathcal{E}_1 \\ \mathcal{E}_2 \\ \vdots \\ \mathcal{E}_T \end{bmatrix}_{NT\times n} \tag{8}$$

where subscript *N* refers to the number of banks in our sample which equals 111 and *T* shows the number of time periods, which is 68, *n* is the subscript denoting the number of endogenous variables and *m* indicates the number of exogenous variables. Each Y_t represents a vector of $y_{i,t}$'s, which are transposed for calculation convenience, at time *t.* Each $y_{i,t}$ is a vector of our four endogenous variables at time *t,* for bank *i* as specified in (11). All the $y_{i,t}$'s at time *t* are then stacked in rows to form Y_t. Similarly, the X_t's are stacked matrices of the lagged endogenous variables and the exogenous variables. *B* is our matrix of coefficients for each of the VAR equations. Similar to Y_t and X_t, each ε_t is also the transpose of the residual values for each equation at time *t*, stacked for the 111 banks. Therefore:

$$Y_t = \begin{bmatrix} y'_{1,t} \\ y'_{2,t} \\ \vdots \\ y'_{N,t} \end{bmatrix} \qquad X_t = \begin{bmatrix} y'_{1,t-1} & \cdots & y'_{1,t-4} & x'_t \\ y'_{2,t-1} & \cdots & y'_{2,t-4} & x'_t \\ \cdots & \ddots & \vdots & \vdots \\ y'_{N,t-1} & \cdots & y'_{N,t-4} & x'_t \end{bmatrix} \qquad \mathcal{E}_t = \begin{bmatrix} \varepsilon'_{1,t} \\ \varepsilon'_{2,t} \\ \vdots \\ \varepsilon'_{N,t} \end{bmatrix} \tag{9}$$

$$B=\begin{bmatrix} A^{(1)} \\ A^{(2)} \\ A^{(3)} \\ A^{(4)} \\ C \end{bmatrix}=\begin{bmatrix} \beta_{1,1}^{(1)} & \cdots & \beta_{1,4}^{(1)} \\ \vdots & \ddots & \vdots \\ \beta_{4,1}^{(1)} & \cdots & \beta_{4,4}^{(1)} \\ \beta_{1,1}^{(2)} & \cdots & \beta_{1,4}^{(2)} \\ \vdots & \ddots & \vdots \\ \beta_{4,1}^{(2)} & \cdots & \beta_{4,4}^{(2)} \\ \beta_{1,1}^{(3)} & \cdots & \beta_{1,4}^{(3)} \\ \vdots & \ddots & \vdots \\ \beta_{4,1}^{(3)} & \cdots & \beta_{4,4}^{(3)} \\ \beta_{1,1}^{(4)} & \cdots & \beta_{1,4}^{(4)} \\ \vdots & \ddots & \vdots \\ \beta_{4,1}^{(4)} & \cdots & \beta_{4,4}^{(4)} \\ c_{1,1} & \cdots & c_{1,4} \\ c_{2,1} & \cdots & c_{2,4} \\ c_{3,1} & \cdots & c_{3,4} \end{bmatrix} \tag{10}$$

with

$$y_{i,t}'=[cap_{i,t} \quad SRISK_{i,t} \quad CAPR1_{i,t} \quad LC_{i,t}] \tag{11}$$

and,

$$x_t'=[termspread_t \quad indpro_t \quad crisis_t] \tag{12}$$

for bank i at time t. Each $A^{(p)}$ is a 4 by 4 matrix of coefficients belonging to lag p of the independent variables and C is the coefficient matrix of the exogenous variables. $\beta_{n,k}^{(p)}$ represents the coefficient for the p^{th} lag of variable n where variable k is the dependent variable. $c_{x,k}$ is the coefficient for the exogenous variable x where variable k is the dependent variable.

For simplicity, equation (7) can be reformulated by vectorising as follows[5]:

$$\underbrace{vec(Y)}_{NnT\times 1} = \underbrace{(I_n \otimes X)}_{NnT\times n(np+m)} \underbrace{vec(B)}_{n(np+m)\times 1} + \underbrace{vec(\mathcal{E})}_{NnT\times 1} \tag{13}$$

[5] The symbol ⊗ refers to the Kronecker product of the two matrices. The Kronecker product A⊗B is a matrix obtained by multiplying each element of A with the matrix B.

or:

$$y = \bar{X}\beta + \varepsilon \tag{14}$$

with:

$$\varepsilon \sim \mathcal{N}(0, \bar{\Sigma}) \tag{15}$$

As specified in (15), the residuals are assumed normally distributed with a mean 0 and variance-covariance matrix $\bar{\Sigma}$. In a pooled panel VAR model the assumptions regarding "cross-subsectional heterogeneity" and "static interdependencies" are relaxed. This means the variance of the residuals is constant across different units and there is no correlation in the residuals across units or different time periods. Therefore, the variance matrix of residuals, $\bar{\Sigma}$, can be represented as follows:

$$\bar{\Sigma} = \Sigma_c \otimes I_{NT} \tag{16}$$

where,

$$\Sigma_c = \mathbb{E}\left(\varepsilon_{i,t}\varepsilon_{i,t}'\right) \ \forall i, \ \ while\ \mathbb{E}\left(\varepsilon_{i,t}\varepsilon_{j,t}'\right) = 0, \ \ for\ i \neq j \tag{17}$$

Therefore, the variance-covariance matrix of the residuals is the Kronecker product of a 4 by 4 variance-covariance matrix of residuals common to all units and an identity matrix of size N×T.

3.3.2. The structural VAR setup and impulse-response functions

We present our results in the format of impulse-response functions (IRFs). Therefore, it is essential to recover the structural innovations (i.e. to orthogonalize the shocks) from the VAR residuals obtained from the VAR represented in (7), or its vectorised equivalent (14). Without doing so, the shocks are very likely to be correlated (the variance-covariance matrix $\bar{\Sigma}$ typically is not diagonal), so it would be impossible to isolate the effect of a single shock. This issue can be overcome using structural VARs. To set up the structural VAR, we first need to estimate the reduced-form model. Our VAR presented in (7) and (14) can be reformulated as follows by taking transposes of the $A^{(p)}$ matrices:

$$y_{i,t} = A'^{(1)}y_{i,t-1} + A'^{(2)}y_{i,t-2} + A'^{(3)}y_{i,t-3} + A'^{(4)}y_{i,t-4} + C'x_t + \varepsilon_{i,t}$$

$$\varepsilon_{i,t} \sim \mathcal{N}(0, \Sigma_c) \tag{18}$$

The vectors $y_{i,t}$ and x_t are defined as in (11) and (12) and the $A'^{(p)}$'s are the transpose of the $A^{(p)}$ matrices as specified in (10). The reduced-form VAR presented above can alternatively be specified as a structural VAR model as follows:

$$D_0 y_{i,t} = D_1 y_{i,t-1} + D_2 y_{i,t-2} + D_3 y_{i,t-3} + D_4 y_{i,t-4} + Fx_t + \eta_{i,t}$$

$$\eta_{i,t} \sim \mathcal{N}(0, \Gamma) \tag{19}$$

where $\eta_{i,t}$ is a vector of structural innovations with the variance-covariance matrix Γ. We aim to have a diagonal Γ, which would mean that our shocks are no more correlated, and therefore we can calculate meaningful impulse-response functions. For a simpler specification, let us assume:

$$D = D_0^{-1} \tag{20}$$

By multiplying both sides of the equation (19) with D, we obtain:

$$A'^{(p)} = DD_i \tag{21}$$

$$C' = DF \tag{22}$$

$$\varepsilon_{i,t} = D\eta_{i,t} \tag{23}$$

According to equation (23), we can consider D as the structural matrix that allows us to recover the structural innovations from the reduced-form VAR residuals. The variance-covariance matrix of residuals, Σ_c, can therefore be expanded as follows:

$$\Sigma_c = \mathbb{E}(\varepsilon_{i,t}\varepsilon'_{i,t}) = \mathbb{E}(D\eta_{i,t}\eta'_{i,t}D') = D\mathbb{E}(\eta_{i,t}\eta'_{i,t})D' = D\Gamma D' \tag{24}$$

Therefore:

$$\Sigma_c = D\Gamma D' \quad (25)$$

In the case of our VAR model, which has 4 endogenous variables, D has 16 elements to identify and Γ has 10 (=4×5/2) unique elements to identify. Therefore, we need 26 restrictions to identify the systemic presented in (25). The variance matrix Σ_c provides only 10 (=4×5/2) restrictions, therefore we need another 16 restrictions to identify D and Γ.

We adopt two different approaches to provide the additional restrictions required to identify the system in (25). First, we use the conventional Cholesky factorisation method. This identification scheme assumes that Γ is diagonal and all the structural shocks have unit variance. Therefore $\Gamma = \mathrm{I}$. Based on this, (25) simplifies to:

$$\Sigma_c = DD' \quad (26)$$

Therefore, we now need 16 restrictions to identify D. So, in addition to the 10 restrictions given by Σ_c, we require 6 more restrictions. This is done by imposing contemporaneous restrictions on the structural shocks. By doing so we assume that some of the variables do not respond contemporaneously to the other variables, which leads to a lower triangular *D.* Therefore, the 6 zero elements of *D* above the main diagonal provide the additional 6 restrictions required. This approach makes the ordering of the variables in our VAR model particularly important. This is because the variables need to be ordered according to their "degree" of endogeneity.

We set up our VAR model with the variables ordered as specified in (11). While the ordering of the variables can be a subjective issue in many cases, we base our choice on the following reasoning. We put market cap first as the most exogenous of our variables. We order systemic risk next, as SRISK is directly affected by equity value as shown in equation (6). Therefore, a shock to a bank's market cap is likely to have a concurrent effect on the bank's systemic risk. The third variable in our model is the risk-adjusted tier 1 capital ratio, as it essentially depends on a bank's equity capital and risk levels (i.e. the previous two variables). The last variable in our model is liquidity creation. Since liquidity creation data is not typically available in real-time, we argue that the other three variables in our model are unlikely to show a contemporaneous reaction to liquidity creation shocks.

As an alternative to Cholesky factorisation, we also use "triangular factorisation" to identify D and Γ in the system presented in (25). In this approach, the assumption regarding the unit variance of all structural shocks is relaxed, and therefore Γ is no more an identity matrix. However, Γ is still a diagonal 4 by 4 matrix, which means that the zeros below the main diagonal provide 6 restrictions out of the 16 required to identify (25). The remaining 10 restrictions are imposed based on the assumption that D is lower triangular and that the variables show a unit response to their own contemporaneous shocks. This means that the elements on the main diagonal of D are equal to 1 while the elements above the main diagonal are zeros. This gives us the additional 10 restrictions required to work out D and Γ. Similar to Cholesky factorisation, the ordering of the variables carries importance in this case too. Therefore, we stick to the same ordering as discussed before in the case for triangular factorisation as well.

3.3.3. Model estimation using Bayesian methods

We adopt a Bayesian VAR approach to estimate the parameters of our model.[6] Bayesian VAR models are now rising in popularity in finance and economics literature because of several important advantages compared to the conventional "frequentist" approach. In Bayesian econometrics, the parameters are assumed to be random variables themselves, therefore, unlike the frequentist approach, there does not exist a "true" parameter value. This gives an advantage to the Bayesian methods especially when there is a relatively small sample size. Because the aim of the estimation in a Bayesian approach is to identify the distribution of the parameters, rather than the "true" point estimate of the parameters, Bayesian methods provide a better measure of estimation uncertainty.

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[6] We run our estimation using BEAR Toolbox on MATLAB developed by Alistair Dieppe, Björn van Roye and Romain Legrand; Available at: https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html

Bayesian econometrics is fundamentally based on what is known as the Bayes' theorem of conditional probability. According to Bayes' theorem, the conditional probability of event A given that B is true can be expressed as:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{27}$$

This relation can be proved mathematically as follows:

$$P(A|B) = \frac{P(A,B)}{P(B)} = \frac{P(A,B)}{P(B)}\frac{P(A)}{P(A)} = \frac{P(B,A)}{P(A)}\frac{P(A)}{P(B)} = \frac{P(B|A)\,P(A)}{P(B)} \tag{28}$$

To define the above relation in a regression context, let us assume that y is our information set and θ is our vector of parameters. Therefore:

$$P(\theta|y) = \frac{f(y|\theta)P(\theta)}{f(y)} \tag{29}$$

In Bayesian context, $P(\theta|y)$ is known as the posterior distribution of the regression parameters. According to the equation above, the posterior distribution is the product of the data likelihood function $f(y|\theta)$ and the "prior distribution" $P(\theta)$, divided by the data density function $f(y)$. The denominator $f(y)$ is independent of θ and only works as a normalising constant in the equation above. Therefore, for the sake of simplicity, equation (29) can be rewritten as:

$$P(\theta|y) \propto f(y|\theta)P(\theta) \tag{30}$$

Based on the relation above, the posterior distribution of any parameter can be obtained by having in hand the data likelihood function and the prior distribution. Fundamentally, this is the ultimate problem in Bayesian estimation of any econometric model. In our VAR framework, the vector of parameters θ can be divided into two main blocks consisting of the VAR coefficients θ and the variance-covariance matrix of the residuals which we denote by Σ. Assuming independence between θ and Σ, the joint distribution of the two blocks would be equal to the product of the two individual densities. Therefore, we can expand (30) as:

$$P(\theta|y) \propto f(y|\theta)P(\theta)P(\Sigma) \quad (31)$$

To determine the posterior distribution of θ, we need to determine the data likelihood function $f(y|\theta)$ and the prior distributions for θ and $\bar{\Sigma}$. As shown in (15), we assume residuals of our panel VAR model to follow a multivariate normal distribution with mean 0 and variance-covariance matrix $\bar{\Sigma}$. This implies that our data vector y also follows the same multivariate normal distribution with mean $\bar{X}\beta$ and variance-covariance matrix $\bar{\Sigma}$. Therefore, based on the PDF of the multivariate normal distribution, the likelihood function can be represented as:

$$f(y|\beta,\bar{\Sigma}) = (2\pi)^{-nT/2}\,|\bar{\Sigma}|^{-1/2}\exp\left[-\frac{1}{2}(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta)\right] \quad (32)$$

We can drop $(2\pi)^{-nT/2}$ from the relation above to reach a simpler proportional relation:

$$f(y|\beta,\bar{\Sigma}) \propto |\bar{\Sigma}|^{-1/2}\exp\left[-\frac{1}{2}(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta)\right] \quad (33)$$

We adopt the commonly used normal-Wishart identification strategy to specify the prior distributions of β and $\bar{\Sigma}$. Based on this approach β is assumed to have a multivariate normal distribution:

$$\beta \sim N(\beta_0, \Sigma_c \otimes \Phi_0) \quad (34)$$

The mean β_0 is a 19 by 1 vector, where the mean values of the estimation parameters are specified. In a normal-Wishart approach (similar to other conventional approaches such as Minnesota) the values of β_0 elements are set around 1 for each variables' own first lag and 0 for higher-order lags as well as cross-variable and exogeneous coefficients. The variance of β is the Kronecker product of two matrices. Σ_c is the variance-covariance matrix of the variables as defined in (17). Φ_0 is a 19 by 19 diagonal matrix that represents the variance-covariance matrix of the estimated parameters for a single equation in the

VAR system. To obtain the variances of the parameters in all the equations, Φ_0 is scaled by the variance of the dependent variable in each equation, which is contained in Σ_c. The Kronecker product in (34) therefore implies that the variance-covariance matrix of the parameters in each equation is proportional to the variance-covariance matrix of the parameters in the other equations. This is a required assumption to obtain a well-identified posterior distribution for β.

We define Φ_0 based on the following strategy (see e.g. Karlsson 2012) For lag terms (both own lags and cross-lags), in the equation for a generic variable *k,* we define the variance as:

$$\sigma^2_{\beta^{(p)}_{n,k}} = \left(\frac{1}{\sigma^2_n}\right)\left(\frac{\lambda_1}{p^{\lambda_3}}\right)^2 \tag{35}$$

Where σ^2_n is the unknown residual variance for variable *n* in the VAR model, which is approximated by individual autoregressive estimations. These regressions are run on pooled samples selected from the 111 sample banks for each variable. λ_1 is the overall variance tightness parameter and λ_3 is a scaling coefficient that determines the speed at which coefficient of the lag terms higher than 1 converges to 0. Following the conventional approach in the literature, we set λ_1 equal to 0.1 and λ_3 as 1. For the remaining elements of Φ_0, we define the variance for the exogenous variables as:

$$\sigma^2_{c_{x,k}} = (\lambda_1\lambda_4)^2 \tag{36}$$

Where λ_4 is typically a large (potentially infinite) variance parameter which is set at 100 in our model. Having defined (35) and (36) we can now form our 19 by 19 Φ_0 matrix which in conjunction with Σ_c provides our prior variance-covariance matrix for β. Therefore, according to the PDF of the multivariate normal distribution, the prior density of β is given by:

$$P(\beta) \propto |\Sigma_c|^{-\frac{k}{2}} \exp\left[-\frac{1}{2}(\beta-\beta_0)'(\Sigma_c \otimes \Phi_0)^{-1}(\beta-\beta_0)\right] \tag{37}$$

Finally, to obtain the posterior distribution of β, we need to specify the prior distribution of Σ_c. Based on the normal-Wishart identification strategy, the prior for Σ_c is inverse Wishart:

$$\Sigma_c \sim \mathcal{IW}(S_0, \alpha_0) \tag{38}$$

Where S_0 is the 4 by 4 scale matrix for the prior and α_0 is prior degrees of freedom. Although the choice for these hyperparameters can be made subjectively based on the researcher's prior information, we adhere to the standard schemes proposed in the literature in this regard. Therefore, following Karlsson (2012), we define S_0 and α_0 as follows:

$$S_0 = (\alpha_0 - n - 1)\begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 \\ 0 & 0 & 0 & \sigma_4^2 \end{bmatrix} \tag{39}$$

$$\alpha_0 = n + 2 \tag{40}$$

The residual variances σ_1^2, σ_2^2, σ_3^2 and σ_4^2 are determined using pooled AR regressions as described earlier in the section. Having S_0 and α_0, the prior density of Σ_c is given by the following relation:

$$P(\Sigma_c) \propto |\Sigma_c|^{-\frac{\alpha_0+n+1}{2}} \exp\left[-\frac{1}{2}\, tr\{\Sigma_c^{-1} S_0\}\right] \tag{41}$$

Where tr denotes the trace function. Now that the data likelihood function and the required prior distribution are specified, we can obtain the posterior distribution on β using the Bayes' theorem as shown in (31):

$$\begin{aligned} P(\beta, \Sigma_c|y) \propto |\Sigma_c|^{-\frac{k}{2}} \exp\left[-\frac{1}{2}\, tr\{\Sigma_c^{-1}[(B - \bar{B})'\bar{\Phi}^{-1}(B - \bar{B})]\}\right] \\ \times |\Sigma_c|^{-\frac{\bar{\alpha}+n+1}{2}} \exp\left[-\frac{1}{2}\, tr\{\Sigma_c^{-1}\bar{S}\}\right] \end{aligned} \tag{42}$$

with:

$$\bar{\Phi} = [\Phi_0^{-1} + X'X]^{-1} \tag{43}$$

$$\bar{B} = \bar{\Phi}[\Phi_0^{-1}B_0 + X'Y] \tag{44}$$

$$\bar{\alpha} = NT + \alpha_0 \tag{45}$$

$$\bar{S} = Y'Y + S_0 + B_0'\Phi_0^{-1}B_0 - \bar{B}'\bar{\Phi}^{-1}\bar{B} \tag{46}$$

where, as specified before, *N* refers to the number of banks in our sample (=111) and *T* is the number of our sample periods (=68). Marginalising for β and Σ, we obtain:

$$P(\Sigma_c|y) \sim \mathcal{IW}(\bar{\alpha}, \bar{S}) \tag{47}$$

and:

$$P(B|y) \sim \mathcal{MT}(\bar{B}, \bar{S}, \bar{\Phi}, \tilde{\alpha}) \tag{48}$$

with:

$$\tilde{\alpha} = \bar{\alpha} - n + 1 = NT + \alpha_0 - n + 1 \tag{49}$$

Expression (48) refers to the matrix-variate student distribution with mean $\bar{B}$, scale matrices $\bar{S}$ and $\bar{\Phi}$ and a degree of freedom equal to $\tilde{\alpha}$. This implies that the individual elements of the coefficients' matrix *B,* all follow a univariate student's t distribution. In the next section, we present and discuss the results from estimating our Bayesian panel VAR model as elaborated.

4. Results Discussion

4.1. Preliminary analysis

Our purpose in this study is to investigate the dynamics between bank systemic risk and different liquidity creation measures. **Table 1** provides summary statistics of the endogenous variables we include in our VAR models while **Table 2** presents the correlation matrix of the variables. As the numbers indicate, the average SRISK value for a bank in our sample is approximately \$709 million.

This means that an average bank in our sample would face a capital shortfall of about $709 million in case of a crisis, based on our sample period data. The average liquidity creation by our sample banks in each quarter is almost $25 billion, where about $14.5 billion of it takes place off-balance sheet. Within on-balance sheet items, liabilities side liquidity creation carries a remarkably higher weight than assets-side liquidity creation, which is negative on average for our sample.

Table 1 – Descriptive statistics of the variables

	Mean	*Median*	*Std Deviation*	*Min*	*Max*	*Skewness*	*Kurtosis*
SRISK	709.30	-15.77	9567.82	-47510.81	158000.18	8.89	100.18
catfat	24735.38	1390.21	107934.30	-79911.04	1202553.93	6.61	50.54
catnonfat	10222.37	1046.92	42982.96	-111804.30	481896.50	6.94	59.43
LC_OBS	14513.02	322.48	74618.39	-14.59	925154.83	7.86	71.42
LC_A	-1281.16	252.66	27879.76	-417609.03	110317.29	-9.35	110.72
LC_L	11503.53	761.95	51183.56	-3477.31	516532.15	6.94	54.34

Notes: The table presents the summary statistics of the main variables studied in this paper. SRISK is our measure of systemic risk, 'catfat' is total liquidity creation, 'catnonfat' is on-balance sheet liquidity creation, 'LC_OBS' is off-balance sheet liquidity creation, ' LC_A' is asset-side liquidity creation and 'LC_L' is liabilities-side liquidity creation. The values are in million US dollars.

The estimated correlation coefficients presented in **Table 2** indicate a significant correlation among nearly all of our variables. Systemic risk is positively correlated with all types of liquidity creation except for assets-side liquidity creation. This implies that different components of a bank's liquidity creation activities can have different effects on the bank's risk levels. Breaking down the different components of total liquidity creation, we can see that *catnonfat* and *LC_OBS* have a positive correlation coefficient of about 66 percent. This is while the two components of on-balance sheet liquidity creation, namely assets-side (*LC_A*) *and* liabilities-side (*LC_L*) liquidity creation, are negatively correlated at about -54 percent.

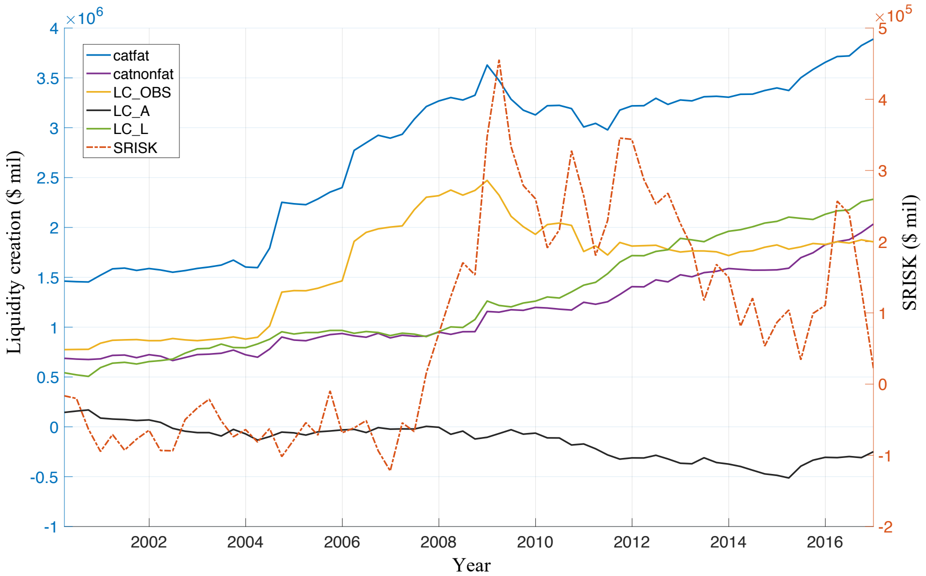
To have a better overview of how our variables have evolved during our sample period, **Figure 1** displays the time-series plots of the aggregate values for SRISK and the five measures of liquidity creation under examination for our 111 sample banks. All of our liquidity creation measures, excluding assets-side liquidity creation, have increased in value during the sample period. However, a major fraction of this increase, particularly in the years leading to the 2008-2009 financial crisis, has resulted from substantial rises in off-balance sheet liquidity creation. The significant increase in *LC_OBS* in pre-crisis and crisis years, when SRISK values peak, provides an early indication that increased off-balance sheet liquidity creation has been associated with a destabilised financial system.

Table 2 – Correlation matrix of the variables

	SRISK	*catfat*	*catnonfat*	*LC_OBS*	*LC_A*	*LC_L*
SRISK	1.0000 *(1.00)*					
catfat	0.6460 *(0.00)*	1.0000 *(1.00)*				
catnonfat	0.3977 *(0.00)*	0.8546 *(0.00)*	1.0000 *(1.00)*			
LC_OBS	0.7053 *(0.00)*	0.9542 *(0.00)*	0.6601 *(0.00)*	1.0000 *(1.00)*		
LC_A	-0.6001 *(0.00)*	-0.4230 *(0.00)*	0.0021 *(0.85)*	-0.6131 *(0.00)*	1.0000 *(1.00)*	
LC_L	0.6608 *(0.00)*	0.9481 *(0.00)*	0.8386 *(0.00)*	0.8883 *(0.00)*	-0.5429 *(0.00)*	1.0000 *(1.00)*

Notes: : The table presents the correlation coefficients between the main variables studied in this paper. 'SRISK' is our measure of systemic risk, 'catfat' is total liquidity creation, 'catnonfat' is on-balance sheet liquidity creation, 'LC_OBS' is off-balance sheet liquidity creation, ' LC_A' is asset-side liquidity creation and 'LC_L' is liabilities-side liquidity creation. Numbers in the parentheses represent the p-values.

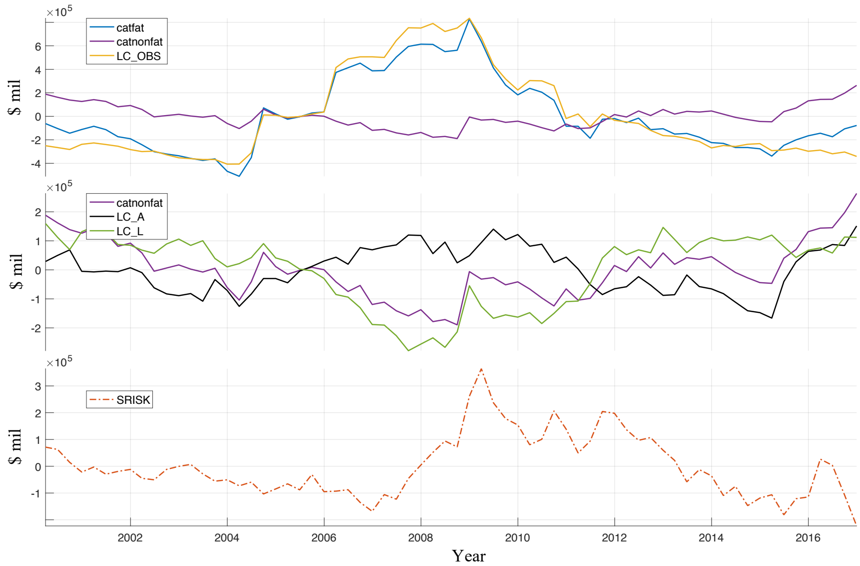
Figure 1 - Systemic risk vs liquidity creation



Notes: The figure draws a comparison between the total liquidity creation and its components and the total SRISK of our sample firms during the sample period 2000-2016. The left-side y axis represents the values for the liquidity creation measures while the right-side y axis represents the values for SRISK. 'SRISK' is our measure of systemic risk, 'catfat' is total liquidity creation, 'catnonfat' is on-balance sheet liquidity creation, 'LC_OBS' is off-balance sheet liquidity creation, ' LC_A' is asset-side liquidity creation and 'LC_L' is liabilities-side liquidity creation. All values are in million US dollars.

To investigate how systemic risk and liquidity creation levels fluctuated regardless of the economic trends that might drive the variables over time, we plot the detrended variables in a stacked plot presented in **Figure 2**. Similar to the previous plot, **Figure 2** suggests that *LC_OBS* has had the highest level of co-movements with SRISK, being the main driver of substantial increases in total liquidity creation levels in the 2006-2010 period.

Figure 2 - Systemic risk vs liquidity creation (detrended)



Notes: The figure exhibits the stacked detrended time-series plots of the five liquidity creation measures and total SRISK for the financial institutions under study during the sample period 2000-2016. The top graph shows 'catfat' and its two components, the middle graph shows 'catnonfat' and its two components, and the bottom graph displays SRSIK. The y axes in the top two graphs represent the values for the liquidity creation measures while the y axis in the bottom graph represents the values for SRISK. 'SRISK' is our measure of systemic risk, 'catfat' is total liquidity creation, 'catnonfat' is on-balance sheet liquidity creation, 'LC_OBS' is off-balance sheet liquidity creation, ' LC_A' is asset-side liquidity creation and 'LC_L' is liabilities-side liquidity creation. All values are in million US dollars.

4.2. Panel VAR estimation results

In this section, we run the panel VAR estimations using five different measures of liquidity creation introduced by Berger and Bouwman (2009). For the first stage of the analysis, we use the aggregate measure of liquidity creation c*atfat,* which consists of both on-balance sheet and off-balance sheet activities. In the second stage of the analysis, we consider on-balance sheet *(catnonfat)* and off-balance sheet *(LC_OBS)* liquidity creation separately, to test whether they have different dynamics with bank systemic risk. Lastly, we decompose the on-balance sheet liquidity creation into asset-side (*LC_A*) and liabilities side (*LC_L*) liquidity creation and run our VAR model separately for each. Due to the high correlation between the different measures of liquidity creation, we estimate our VAR models individually with each measure. For the sake of brevity, we only report the results in the form of impulse-response functions and exclude the estimated regression parameters.

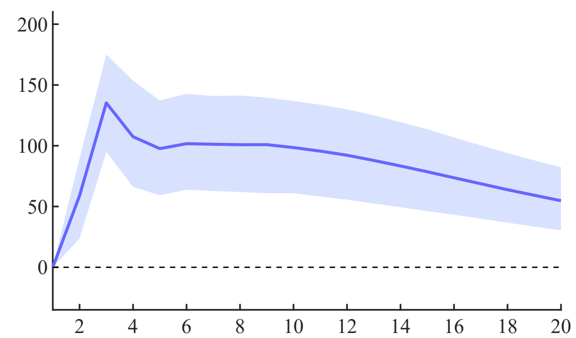
4.2.1. Systemic risk and total liquidity creation

Figure 3 presents the impulse-response functions of our panel VAR model with the aggregate measure of liquidity creation *catfat.* The estimations are done using Bayesian panel VAR techniques explained in section3.3. Panel A presents the response of systemic risk to *catfat* shocks and panel B displays the response of *catfat* to systemic risk shocks.

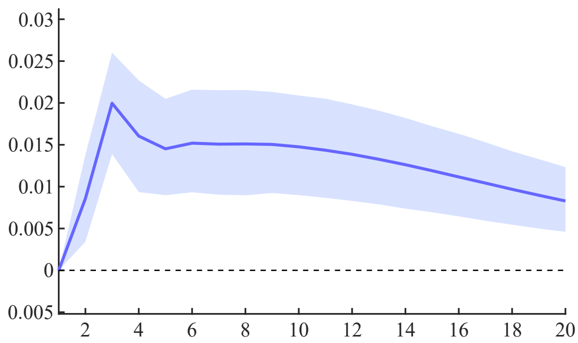
Figure 3 – Impulse responses of SRISK and total liquidity creation

Panel A — Impulse *catfat* – Response *SRISK*

Cholesky factorisation

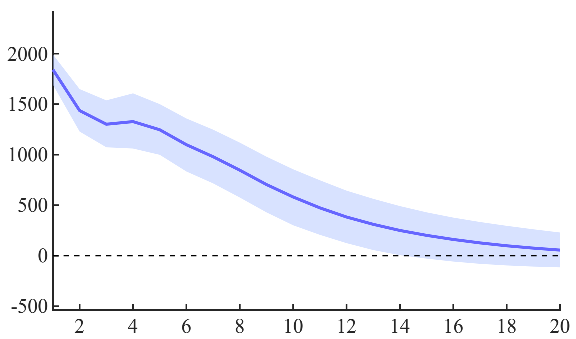


Triangular factorisation

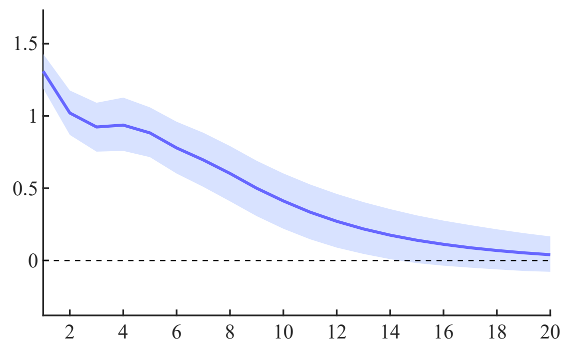


Panel B — Impulse *SRISK* – Response *catfat*

Cholesky factorisation



Triangular factorisation



*Notes: The graphs present the estimated structural impulse-response functions based on the panel VAR model explained in section **3.3**, with the endogenous variables: cap, SRISK, CAPR1, and catfat (with 4 lags). The graphs are presented for two of the endogenous variables only, namely SRISK and catfat. Panel A shows the response of SRISK to catfat, while Panel B shows the response of catfat to SRISK. The blue lines represent the median from the estimated posterior distributions of the responses and the shaded areas indicate the 95% confidence (credibility) intervals. The graphs on the left present the results of the model with Cholesky restrictions and the graphs on the right present results of the model with triangular restrictions. The sample period is 2000Q1 to 2016Q4.*

The graphs exhibit the responses for 20 quarters (5 years) ahead, as a result of a shock to the impulse variable. The shaded areas represent the 95 percent confidence (credibility) interval for the estimated responses. We assume a response to be statistically significant if zero lies outside the 95 percent confidence interval.

Each column in **Figure 3** presents the IRFs obtained via one of the two structural identification schemes explained in section **3.3.2**. The results from Cholesky factorisation report the responses to a one-standard-deviation shock to the impulse variable while triangular factorisation shows the responses to a one-unit shock to the impulse variable. This is because in the Cholesky identification scheme the shocks are assumed to have unit variance, so a one-unit increase in the structural innovation term corresponds to a one-standard-deviation increase. However, in the triangular factorisation approach, the shocks are allowed to have different variances and are not standardised, therefore, each shock implies a one-unit increase in the impulse variable, which in our case is equal to $1 million.

The graph in panel A in **Figure 3** suggest that *catfat* has a highly significant and long-lasting positive effect on SRISK. A one standard deviation shock to total liquidity creation causes about $135.3 million increase in systemic risk three quarters later when the response is the strongest. Since *SRISK* estimates the amount of capital shortfall in case of a crisis, this means that a positive shock to liquidity creation can on average cause a bank to be undercapitalised by about $127 million if a crisis happens. The positive effect of a *catfat* shock on SRISK remains positive and significant for the entire 20 quarters, although it starts to diminish gradually after the 7th quarter. This finding is consistent with our "leverage risk" hypothesis and the findings of Berger and Bouwman (2017) and Fungacova, Turk, and Weill (2015), who document a destabilising effect of liquidity creation on banks. The IRFs obtained via triangular factorisation also exhibit similar results to those of Cholesky factorisation. Based on the top right graph in **Figure 3**, a $1 million shock to a bank's total liquidity creation leads to significant increases in the bank's systemic risk peaking at approximately $20,000 in the third quarter.

The bottom panel in **Figure 3** presents the responses of total liquidity creation to systemic risk shocks. The graph on the left column indicates that a one standard deviation positive shock to SRISK causes a significant rise in *catfat* up until the 14th lag. The response starts with a contemporaneous increase of about $1.8 billion which gradually decreases to almost zero in the 14th quarter. According to the results generated via triangular factorisation, a $1 million shock to a bank's SRISK level causes an immediate increase of almost $1.3 million in the bank's total liquidity creation, which gradually decreases to become statistically insignificant from the 14th period onwards.

These findings are in line with our "relaxed borrowing conditions" hypothesis, where we argue that increased levels of systemic risk expose banks to higher threat of fire sales, and thus relax the borrowing conditions for the banks. Our results also provide empirical evidence to the theoretical model discussed by Morrison and Walther (2020). Based on this model, banks tend to deliberately inflate their levels of systemic risk (by investing in the 'aggregate sector') to take advantage of lower borrowing restrictions, because a higher threat of fire-sales makes the lenders more confident in the bank's asset choices.

4.2.2. Systemic risk and on-/off-balance sheet liquidity creation

On-balance sheet and off-balance sheet liquidity creation each constitute about half of the total liquidity creation in the US (Berger and Bouwman 2015). The graph presented in **Figure 1** shows that off-balance sheet activities have gained a bigger share of total liquidity creation before and during the crisis years. To investigate the interactions between bank systemic risk and the two main components of bank liquidity creation, we run our panel VAR model separately with *catnonfat* and *LC_OBS* replaced with *catfat.* We control for the same variables as in the previous model.

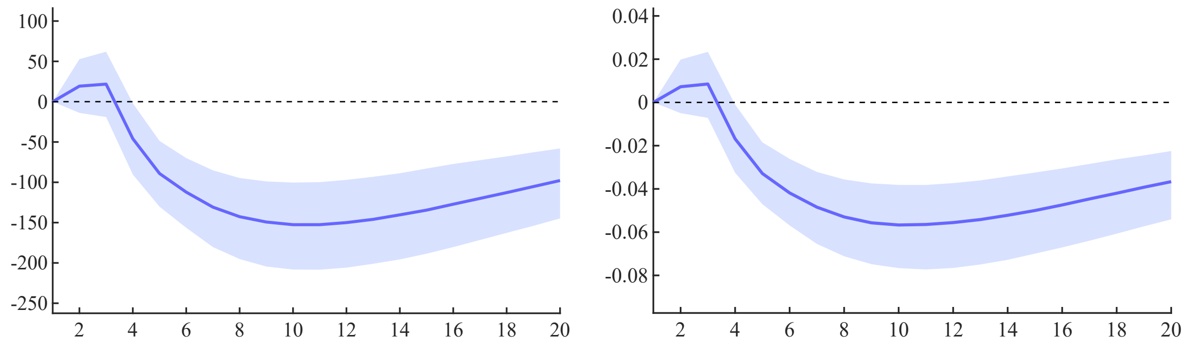
Figure 4 and **Figure 5** summarise the graphs that exhibit the response of SRISK to shocks to on-balance sheet and off-balance sheet liquidity creation and vice versa. For the sake of better analogy, we first discuss the top panels of both figures (i.e. the response of SRSIK) before we analyse the bottom panels (i.e. the response of liquidity creation). The response of SRISK to *catnonfat* shocks is not significantly different from zero until the 4th lag following the shock. However, after the 4th lag, the response of SRISK starts to become significantly negative, reaching its minimum level on the 10th lag.

The results imply that a one-standard-deviation shock to *catnonfat* can lead to an average reduction of about \$152 million in a bank's SRISK levels in two and a half years. This corresponds to an approximately \$57,000 reduction in the SRISK value on the 10th lag, as a result of a \$1 million shock to on-balance sheet liquidity creation.

Figure 4 – Impulse responses of SRISK and on-balance sheet liquidity creation

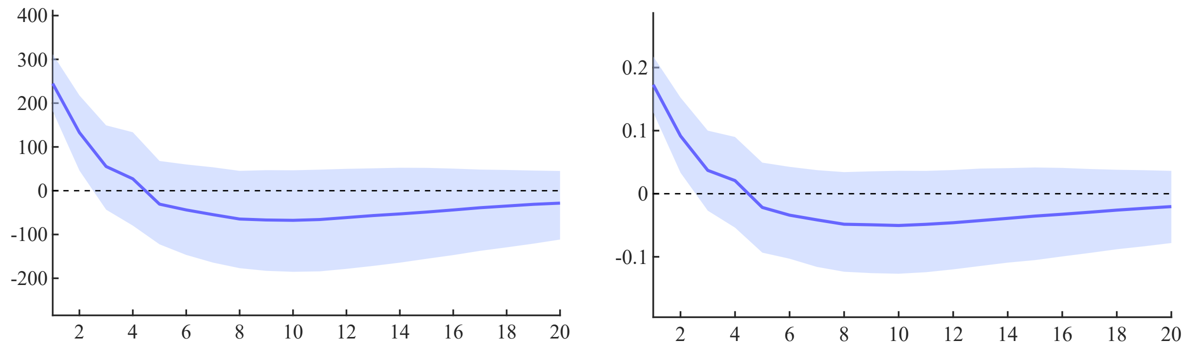
Panel A — Impulse *catnonfat* – Response *SRISK*

Cholesky factorisation — Triangular factorisation



Panel B — Impulse *SRISK* – Response *catnonfat*

Cholesky factorisation — Triangular factorisation



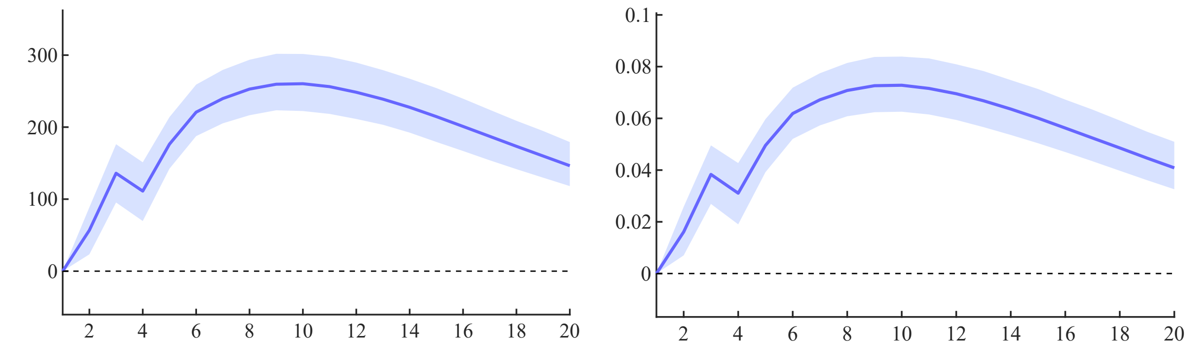
Notes: The graphs present the estimated structural impulse-response functions based on the panel VAR model explained in section ***3.3****, with the endogenous variables: cap, SRISK, CAPR1, and catnonfat (with 4 lags). The graphs are presented for two of the endogenous variables only, namely SRISK and catnonfat. Panel A shows the response of SRISK to catnonfat, while Panel B shows the response of catnonfat to SRISK. The blue lines represent the median from the estimated posterior distributions of the responses and the shaded areas indicate the 95% confidence (credibility) intervals. The graphs on the left present the results of the model with Cholesky restrictions and the graphs on the right present results of the model with triangular restrictions. The sample period is 2000Q1 to 2016Q4.*

The estimated IRFs for off-balance sheet liquidity creation in **Figure 5** provide evidence that the main component of a bank's total liquidity creation that contributes to systemic risk is off-balance sheet liquidity creation. Shocks to *LC_OBS* tend to have a long-lasting and significant positive impact on SRISK. The response of SRISK is strongest in the 10th quarter when it reaches above \$260 million for a one-standard-deviation shock (parallel to an approximately $73,000 increase in response to a $1 million shock). Therefore, the overall response of SRISK to *LC_OBS* seems to be larger in scale compared to its response to *catnonfat.* These results corroborate those of Berger and Bouwman (2017) suggesting a stronger role of off-balance sheet liquidity creation in predicting crises. However, unlike previous findings, our results suggest that on-balance sheet liquidity creation can have a stabilising effect on the banks.

Figure 5 – Impulse responses of SRISK and off-balance sheet liquidity creation

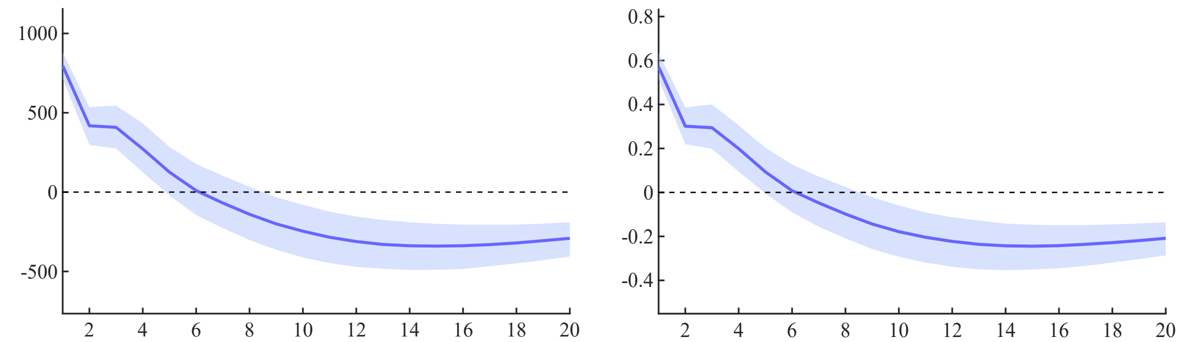
Panel A — Impulse *LC_OBS* – Response *SRISK*

Cholesky factorisation	Triangular factorisation



Panel B — Impulse *SRISK* – Response *LC_OBS*

Cholesky factorisation	Triangular factorisation



*Notes: The graphs present the estimated structural impulse-response functions based on the panel VAR model explained in section **3.3**, with the endogenous variables: cap, SRISK, CAPR1, and LC_OBS (with 4 lags). The graphs are presented for two of the endogenous variables only, namely SRISK and LC_OBS. Panel A shows the response of SRISK to LC_OBS, while Panel B shows the response of LC_OBS to SRISK. The blue lines represent the median from the estimated posterior distributions of the responses and the shaded areas indicate the 95% confidence (credibility) intervals. The graphs on the left present the results of the model with Cholesky restrictions and the graphs on the right present results of the model with triangular restrictions. The sample period is 2000Q1 to 2016Q4.*

On-balance sheet liquidity creation mainly comprises of items such as customer deposits and commercial and real estate loans. (i.e. higher deposits and higher loans both increase the on-balance sheet liquidity creation (Berger and Bouwman 2009)). Depositors and creditors are the main enforcers of market discipline on the banks as they penalise the banks for taking inappropriate risks (see for instance: Demirgüç-Kunt and Huizinga 2004; Karas, Pyle, and Schoors 2013, 2019; Martinez Peria and Schmukler 2001; Morgan and Stiroh 2001). Therefore, the negative effect of on-balance sheet liquidity creation on bank systemic risk can be due to the increased market discipline that arguably comes in tandem with higher on-balance sheet liquidity creation. The results presented in **Figure 6** and **Figure 7** provide further evidence in this regard, which is discussed in the remainder of this section.

Thus, our findings in this section provide evidence to both our "leverage and lending risk" and "market discipline" hypotheses, depending on which component of liquidity creation is being considered. The reduction of systemic risk following shocks to *catnonfat* is in line with the "market discipline" hypothesis, which argues that this reduction could be due to stricter market discipline and/or better risk management by bank managers following rises to liquidity creation.

On the other hand, the results related to *LC_OBS* creation are in accordance with our "leverage and lending risk" hypothesis. Off-balance sheet liquidity creation increases as the bank issues more illiquid guarantees such as commercial and standby letters of credit. Holding liquid derivatives such as interest rate or foreign exchange derivatives, on the other hand, reduces off-balance sheet liquidity creation. Since leverage is not affected by off-balance sheet activities, our result is likely to be driven by excessive risk taking through off-balance sheet activities. Off-balance sheet banking activities are subject to less government regulation and can be regarded as a threat to the banking system stability if a negative systemic shock occurs. Acharya, Schnabl, and Suarez (2013) document that off-balance sheet securitisation of asset-backed commercial paper conduits by banks did not effectively transfer risk to outside investors and resulted in exacerbated bank losses during the 2007-2009 crisis. However, our findings are contradictory to some previous studies that suggest off-balance sheet activities can enhance market discipline and reduce banks' risk (Angbazo 1997; Boot and Thakor 1991; Hassan 1993; Hassan, Karels, and Peterson 1994).

When it comes to the effect of systemic risk on the two types of liquidity creation, which is illustrated on the bottom panels of **Figure 4** and **Figure 5**, we see that the initial response of both *catnonfat* and *LC_OBS* to SRISK shocks is positive, with the response of *LC_OBS* being larger. A one-standard-deviation ($1 million) shock to SRISK is associated with an immediate increase of nearly $245 million ($173,000) in on balance-sheet liquidity creation and almost $800 million ($571,000) increase in the off-balance sheet liquidity creation. The response of *catnonfat* to SRISK shocks is rather short-lived and becomes insignificant after the 2nd lag. On the other hand, the response of *LC_OBS* remains significant and positive for five lags and, after the 9th lag, it starts to become significantly negative. This behaviour could be explained by a feedback effect scenario: as off-balance sheet liquidity creation is a significant contributor to systemic risk, to contain their systemic risk levels, banks tend to reduce their off-balance sheet activities following a shock to their systemic risk. However, such response seems to occur with a lag of almost two years. Overall, comparing the IRFs in **Figure 3**, **Figure 4** and **Figure 5** reveals that the interactions of the two components of *catfat* with SRISK differ from the interactions of *catfat* itself with SRISK.

Similar to the previous case, our findings on the response of SRISK to the two components of total liquidity creation are aligned with both our "relaxed borrowing conditions" and "prudential balance sheet adjustment" hypotheses, depending on the type of liquidity creation and the time frame we focus on. The initial positive response of *catnonfat* to SRISK shocks provides support to the "relaxed borrowing conditions" hypothesis, which argues that a high level of systemic risk could make borrowing easier for the banks (Morrison and Walther 2020).

With respect to off-balance sheet liquidity creation however, since borrowing does not happen off-balance sheet, the initial positive effect is potentially due to an increase in issuing illiquid guarantees by the bank. The eased borrowing conditions and increased cash inflow can encourage banks to issue more illiquid off-balance sheet guarantees, as the abundance of cash resources can mitigate the counterparty risk associated with the illiquid guarantees. Koppenhaver and Stover (1991) show that better capitalised banks tend to issue more standing letters of credit, which comprise a main component of off-balance sheet liquidity creation.

However, in the long-run, the findings regarding the effects of systemic risk on *LC_OBS*, are analogous to our "prudential balance sheet adjustment" narrative. The significant reduction in off-balance sheet liquidity creation nine quarters following shocks to systemic risk implies that, to reduce systemic risk exposure, banks tend to cut their off-balance sheet activities more than their on-balance sheet activities (since the same effect is not observed for *catnonfat*).

4.2.3. Systemic risk and assets-side/liabilities-side liquidity creation

In the final stage of our analysis, we break down on-balance sheet liquidity creation into assets-side (*LC_A*) and liabilities-side (*LC_L*) liquidity creation and run our Bayesian panel VAR model with each measure. **Figure 6** and **Figure 7** present the IRFs for the two VAR models with *LC_A* and *LC_L.* While *LC_A* has a long-lasting positive effect on SRISK like that of *catfat,* the effect of *LC_L* on SRISK changes from positive to negative after the 4^{th} lag. The positive impact of both *LC_A* and *LC_L* peaks on the 3^{rd} lag, where SRISK increases approximately by \$81 million and \$93 million as a result of a one-standard-deviation shock to *LC_A* and *LC_L* respectively.

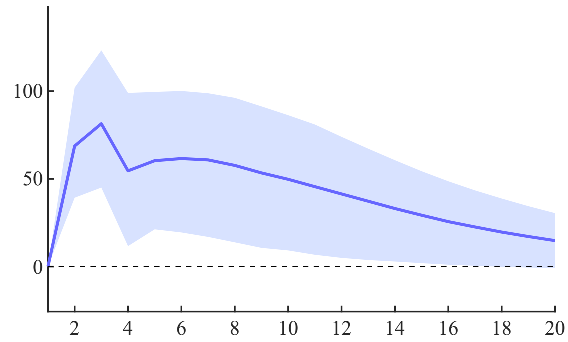
The positive response of SRISK to assets-side liquidity creation is quite analogous to that of total liquidity creation. This suggests that a rise in different types of commercial and industrial lending by banks leads to increased levels of systemic risk ("leverage and lending risk" hypothesis), which can potentially be due to lower lending standards (Acharya and Naqvi 2012). On the other hand, this finding implies that holding liquid assets such as cash and securities as well as Federal funds lending are deemed to reduce systemic risk.

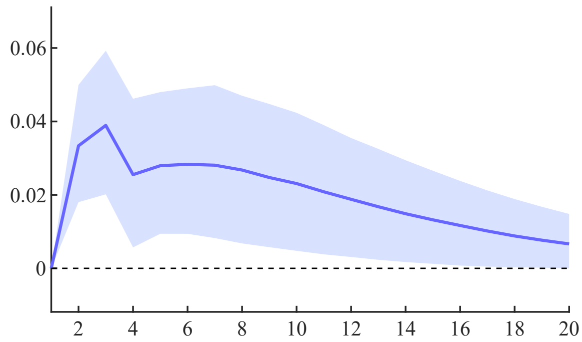
With regards to the response of SRISK to *LC_L*, the results show an initial positive response up to the 5^{th} lag. Higher liabilities-side liquidity creation can increase systemic risk in multiple ways. As discussed earlier, increased leverage is known to be a major contributor to bank fragility. In the meantime, in a ceteris paribus condition, a drop in the equity value of a bank contributes to the systemic risk level of the bank according to the definition provided in equation (6). Therefore, a shock to *LC_L,* leads to significantly higher SRISK values in the period between 6 to 12 months following the shock. This, again, provides support to our "leverage and lending risk" hypothesis.

Figure 6 – Impulse responses of SRISK and assets-side liquidity creation

Panel A — Impulse *LC_A* – Response *SRISK*

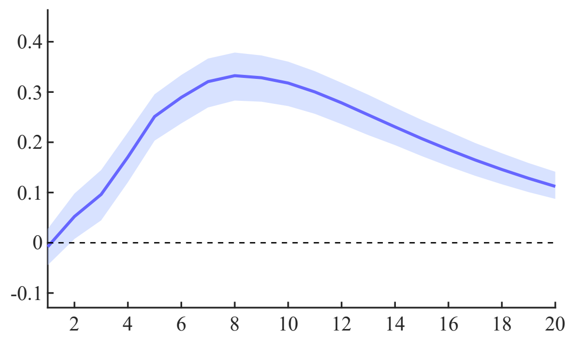
Cholesky factorisation	Triangular factorisation

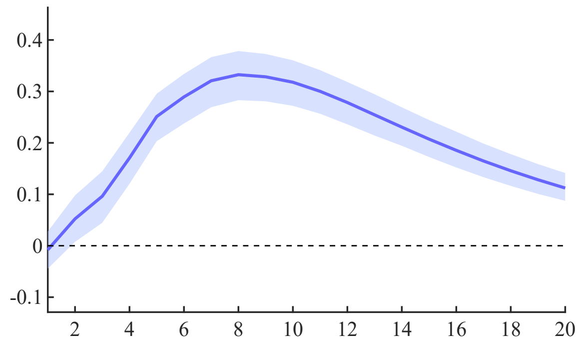




Panel B — Impulse *SRISK* – Response *LC_A*

Cholesky factorisation	Triangular factorisation



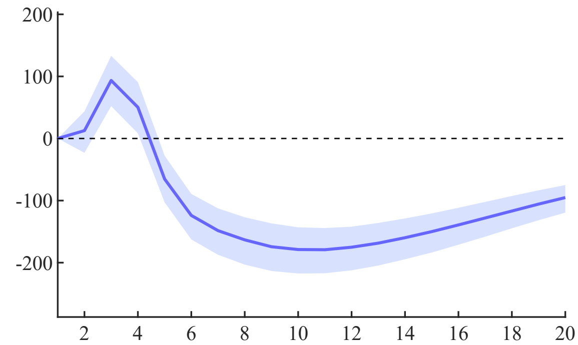
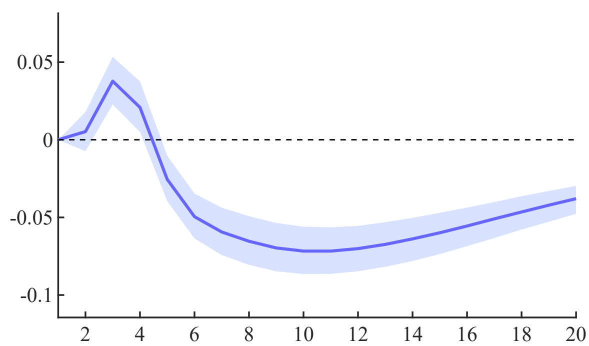


*Notes: The graphs present the estimated structural impulse-response functions based on the panel VAR model explained in section **3.3**, with the endogenous variables: cap, SRISK, CAPR1, and LC_A (with 4 lags). The graphs are presented for two of the endogenous variables only, namely SRISK and LC_A. Panel A shows the response of SRISK to LC_A, while Panel B shows the response of LC_A to SRISK. The blue lines represent the median from the estimated posterior distributions of the responses and the shaded areas indicate the 95% confidence (credibility) intervals. The graphs on the left present the results of the model with Cholesky restrictions and the graphs on the right present results of the model with triangular restrictions. The sample period is 2000Q1 to 2016Q4.*

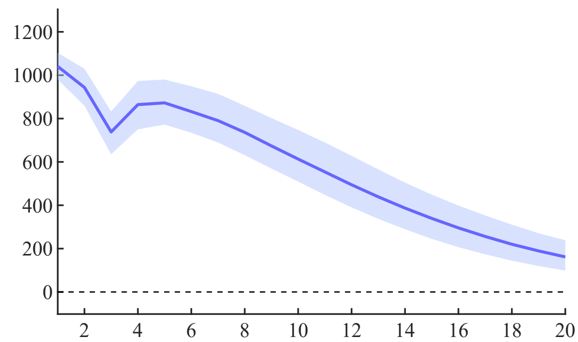
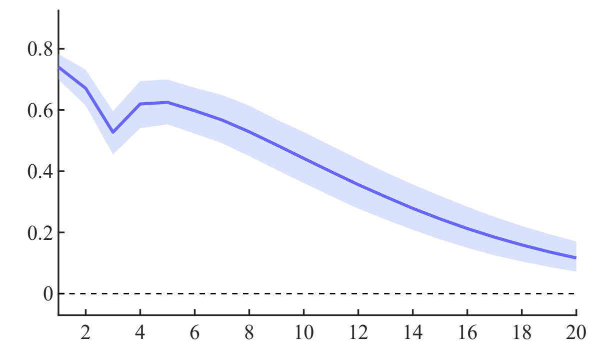
However, the graphs show that the short-tun positive effect turns into negative in the medium to long run. Therefore, in longer time spans, the narrative elaborated in the "market discipline" hypothesis seems to explain our results. Higher debtholder discipline and the threat of facing regulatory and supervisory restrictions can encourage bank managers to contain the banks' systemic risk levels following a 2- to 3-year period of systemic risk upsurge. Moreover, these results suggest that the negative impact of *catnonfat* on SRISK, is predominantly driven by *LC_L*.

Figure 7 – Impulse responses of SRISK and liabilities-side liquidity creation

Panel A — Impulse *LC_L* – Response *SRISK*

Cholesky factorisation	Triangular factorisation
	

Panel B — Impulse *SRISK* – Response *LC_L*

Cholesky factorisation	Triangular factorisation
	

*Notes: The graphs present the estimated structural impulse-response functions based on the panel VAR model explained in section **3.3**, with the endogenous variables: cap, SRISK, CAPR1, and LC_L (with 4 lags). The graphs are presented for two of the endogenous variables only, namely SRISK and LC_L. Panel A shows the response of SRISK to LC_L, while Panel B shows the response of LC_L to SRISK. The blue lines represent the median from the estimated posterior distributions of the responses and the shaded areas indicate the 95% confidence (credibility) intervals. The graphs on the left present the results of the model with Cholesky restrictions and the graphs on the right present results of the model with triangular restrictions. The sample period is 2000Q1 to 2016Q4.*

The panel B graphs in **Figure 6** and **Figure 7** show that the responses of *LC_A* and *LC_L* to SRISK are both mainly significant and positive, although the response of *LC_L* is relatively larger. A one-standard-deviation ($1 million) shock to SRISK is associated with a concomitant rise of nearly $1 billion ($740,000) in *LC_L*. This is a remarkable reaction compared to the rest of our results. The positive response of *LC_A* however exhibits itself with a longer delay. The biggest rise in *LC_A* value following a shock to SRISK takes place on the 8th lag when it reaches about $470 million ($332,000) in response to a one-standard-deviation ($1 million) shock. Regardless of the timing of the response, almost all our estimated IRFs for total liquidity creation and its different components suggest that shocks to systemic risk tend to increase liquidity creation by the banks. Therefore, our arguments related to the "relaxed borrowing conditions" hypothesis seem to be widely supported by empirical evidence.

5. Study limitations and further research

The purpose of this study is to investigate the bidirectional relationship between bank systemic risk and liquidity creation. We conducted our analyses using a sophisticated methodology and extensive estimations to properly address our research questions. However, our study still faces a number of limitations which can possibly be addressed in future research.

Firstly, we aimed to have a large and wide-ranging sample of banks over a relatively long sample period to be able to achieve broad and comprehensive results. Although we do control for size and monetary and macroeconomic stance of the economy, it could be informative to examine large vs small banks and/or various macroeconomic conditions separately. Particularly focusing on the crisis and post-crisis periods and the periods of unconventional monetary policy implementation could reveal important information about financial stability and the policy actions in such periods.

Second, although our proposed hypotheses are able to explain the direction of our results, further research is needed to determine the underlying reasons for the exact timing of the observed reactions. Certain policy making procedures and/or market conditions could possibly explain why some reactions take place with a certain lag and last for long periods.

6. Concluding remarks

In this paper, we investigate the dynamics between systemic risk and liquidity creation at the bank level. For this purpose, we use Bayesian panel VAR models to obtain the impulse response functions between systemic risk and various liquidity creation measures.

Our results reveal significant dynamic interactions between bank systemic risk and liquidity creation. We find that shocks to total liquidity creation are a major contributor to bank systemic risk. However, this effect is merely driven by off-balance sheet liquidity creation whereas on-balance sheet liquidity creation tends to reduce bank systemic risk. This partly corroborates the findings of Berger and Bouwman (2017) who show that increases in total banking sector liquidity creation tend to significantly increase the probability of a crisis. They find that this is primarily the effect of off-balance sheet liquidity creation. While our results confirm this finding, we show that in contrast to off-balance sheet liquidity creation, on-balance sheet liquidity creation tends to have a risk-reducing impact on banks.

To gain a deeper insight into the effect of on-balance sheet liquidity creation on systemic risk, we run our panel VAR model individually with each of the two components of on-balance sheet liquidity creation, i.e. assets-side and liabilities-side liquidity creation. We find that, similar to off-balance sheet liquidity creation, assets-side liquidity creation also tends to increase systemic risk. Liabilities-side liquidity creation, however, has a negative impact on systemic risk in the long-run. We explain the negative impact of labilities-side liquidity creation via a market discipline and bank risk management narrative. Customer deposits and higher leverage are known to improve market discipline. Therefore, we argue that the this negative impact is due to the more austere market discipline, which urges bank managers to improve financial resilience of the bank. On the other hand, the positive effect of assets-side liquidity creation on systemic risk can be a result of reduced lending standards associated with higher liquidity creation.

Hence, our findings regarding the effects of different components of bank liquidity creation on systemic risk can be summarised as follows: an increased liquidity creation always contributes to bank's systemic risk, except for when it potentially improves market discipline (i.e., it happens on the liabilities side).

Importantly, we show that the causal relationship between systemic risk and bank liquidity creation is bidirectional. Our results indicate that total bank liquidity creation tends to rise significantly following shocks to systemic risk. This effect is strongest in the case for liabilities-side liquidity creation. We argue that this is because being more exposed to the threat of bank runs and fire sales, relaxes borrowing conditions for the banks (Morrison and Walther 2020), which leads to higher liquidity creation.

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Appendix 1

Table A.1 – Liquidity creation calculation procedure

Step 1: Classify all bank activities as liquid, semi-liquid, or illiquid. For activities other than loans, information on product category and maturity are combined. Due to data limitations, loans are classified entirely by product category.		
Step 2: Assign weights to the activities classified in Step 1.		
ASSETS:		
Illiquid assets (weight = ½)	*Semi-liquid assets (weight = 0)*	*Liquid assets (weight = −½)*
Commercial real estate loans (CRE)	Residential real estate loans (RRE)	Cash and due from other institutions
Loans to finance agricultural production	Consumer loans	All securities (regardless of maturity)
Commercial and industrial loans (C&I)	Loans to depository institutions	Trading assets
Other loans and lease financing receivables	Loans to state and local governments	Fed funds sold
Other real estate owned (OREO)	Loans to foreign governments	
Investment in unconsolidated subsidiaries		
Intangible assets		
Premises		
Other assets		
LIABILITIES PLUS EQUITY:		
Liquid liabilities (weight = ½)	*Semi-liquid liabilities (weight = 0)*	*Illiquid liabilities + equity (weight = − ½)*
Transactions deposits	Time deposits	Subordinated debt
Savings deposits	Other borrowed money	Other liabilities
Overnight federal funds purchased		Equity
Trading liabilities		
OFF-BALANCE SHEET GUARANTEES (notional values):		
Illiquid guarantees (weight = ½)	*Semi-liquid guarantees (weight = 0)*	*Liquid guarantees (weight = −½)*
Unused commitments	Net credit derivatives	Net participations acquired
Net standby letters of credit	Net securities lent	
Commercial and similar letters of credit		
All other off-balance sheet liabilities		
OFF-BALANCE SHEET DERIVATIVES (gross fair values):		
		Liquid derivatives (weight = −½)
		Interest rate derivatives
		Foreign exchange derivatives
		Equity and commodity derivatives

Step 3: Combine bank activities as classified in Step 1 and as weighted in Step 2 to construct the liquidity creation (LC) measure.			
LC=	+½ * illiquid assets	+0 * semi-liquid assets	−½ * liquid assets
	+½ * liquid liabilities	+0 * semi-liquid liabilities	−½ * illiquid liabilities
	+½ * illiquid guarantees	+0 * semi-liquid guarantees	−½ * equity
			−½ * liquid guarantees
			−½ * liquid derivatives

Notes: The table explains the stages undertaken to calculate the liquidity creation measures as introduced by Berger and Bouwman (2009). On-balance sheet and off-balance sheet items are classified into three groups of "illiquid", "semi-liquid" and "liquid" as specified above and then combined according to the weights given at step 3. In the case of total liquidity creation "catfat", all the on-balance sheet and off-balance sheet items are considered, whereas "catnonfat" includes all the on-balance sheet items and "LC_OBS" is comprised on the off-balance sheet items. Similarly, "LC_A" and "LC_L" are constructed by adding together the assets-side and liabilities side items according to the weights indicated in the table.

STUDY III:

COVID-19 Crisis and Risk in the Financial System

Abstract

We investigate the consequences of the COVID-19 pandemic and the government lockdown policies for the idiosyncratic and systemic risk of the large financial institutions in the US. We find that rises in the number of COVID-19 infections have significantly increased the Value-at-Risk (VaR) of the large US financial institutions as well as the VaR of the financial sector as a whole. With respect to systemic risk, our findings show that upsurges in the number of COVID-19 cases have been associated with significant rises in systemic risk for most of the financial institutions we examine. Using the ΔCoVaR and SRISK measures, we show that systemic risk has reached record highs following the COVID-19 crisis. Finally, we document that increases in government stringency to tackle the spread of the virus have resulted in higher idiosyncratic and systemic risk for the financial institutions.

Keywords: COVID-19, systemic risk, tail risk, CoVaR, SRISK

1. Introduction

The outbreak of the novel coronavirus known as SARS-CoV-2, which causes the disease named "COVID-19", has meant the world is faced with unprecedented challenges. COVID-19 was declared a pandemic by the World Health Organisation (WHO) on the 11th of March 2020. Since the first spread of the virus in Wuhan province of China in December 2019, nearly 200 countries have been affected by COVID-19 by the time of writing this article. The outrageous speed in spread of the infection across the world left the policy makers facing a critical dilemma between reducing the public health costs and reducing the economic costs of the pandemic. As of writing date of this study, more than 24 million people across the world are diagnosed with COVID-19 with more 820,000 lives lost (Roser et al. 2020).

As a result of the alarming increase in the number of infected cases and the death toll, governments around the globe have resorted to various restrictive measures to slowdown the spread of the disease. These measures were mainly based on school, university and business closures, travel restrictions and house lockdowns as well as the "social distancing" rules put in place in the later stages of the pandemic. Although, the "lockdown" policies have so far been relatively successful in containing the spread of the virus, the economic costs of the disruption have been substantial. According to the projections by the Organisation for Economic Co-operation and Development (OECD), in a best-case scenario, where a second wave of infections is avoided, global economic activity is expected to fall 6% in 2020. This number can reach as high as 7.6% if a second wave occurs. With either scenario, it is unexpected for the global economy to be back at 2019-Q4 levels for at least two years (OECD 2020).

Being aware of the detrimental consequences of the COVID-19 pandemic for the economy, governments and central banks have implemented various expansionary policies to stimulate economic activity while business operations are significantly hampered. In March 2020, the Coronavirus Aid, Relief and Economic Security (CARES) Act, was passed by the US Congress and signed by President Donald Trump to tackle the economic plummet caused by COVID-19, via injecting $2.2 trillion into the economy. In the same month, the Federal Reserve announced two rate cuts, lowering the Federal funds target rate from the 1.5% - 1.75% channel to 0.00% - 0.25%.

In addition to the conventional monetary policy interventions, the Fed has also initiated programmes such as the "Paycheck Protection Program" and the "Main Street Lending Program" to facilitate lending and provide credit to small and medium sized businesses. The Fed's balance sheet has expanded considerably during the COVID-19 crisis, reaching over $7 trillion from approximately $4 trillion in the beginning of 2020. Moreover, to provide further assistance to banking operations and the flow of credit, the Fed has taken steps to ease the bank supervisory and regulatory requirements, such as leverage ratio requirements and bank examinations. In addition, in March 2020, the reserve requirements for depository institutions were reduced to zero percent, to support the flow of credit to firms and households.[1]

While the abovementioned policies can be effective in tackling the initial slump in the economy, they might pose unwanted threats on the financial stability in the longer run. A large build-up of consumer debt and reduced scrutiny can lead to a more fragile financial system (see for instance: Ivashina and Scharfstein 2010; Guttmann and Plihon 2010; Schularick and Taylor 2012; Eichengreen and Mitchener 2004; Claessens et al. 2010; Fratzscher, König, and Lambert 2016) , especially when unemployment is at record highs and there is a high level of consumer credit risk. Schularick, Steffen, and Tröger (2020) estimate a potential capital shortfall of up to €600 billion within the European banking sector as a result of the COVID-19 crisis. The role of systemic risk is particularly important in this situation. When systemic risk within the financial system is high, failure of one institution can put the entire system in serious distress.

In this paper, our main goal is to examine the overall stability of the financial system in the wake of the COVID-19 crisis. Our focus is on the impact of the pandemic itself and the government responses that deal with containing the virus spread, rather than the subsequent economic policy actions. For this purpose, we investigate how the systemic risk of large financial institutions has been affected by the number of new COVID-19 cases and the lockdown measures. In addition, we analyse the idiosyncratic

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[1] https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315b.htm

tail risk of the financial institutions and the financial system as a whole. Our findings suggest that the number of new daily COVID-19 cases have caused a significant rise in the systemic and idiosyncratic risk of the large financial institutions.

As shown in **Figure 1** and **Figure 2**, the aggregate US financial sector systemic risk, measured by the SRISK index (Acharya, Engle, and Richardson 2012), has sharply increased shortly after the first COVID-19 case was identified in the US on the 21st of January 2020. Early studies have documented significant rises in the stock market volatility as well as increases in financial contagion and systemic risk across multiple countries (see for instance: Onali 2020; Akhtaruzzaman, Boubaker, and Sensoy 2020; Zhang, Hu, and Ji 2020; Baumöhl et al. 2020; Rizwan, Ahmad, and Ashraf 2020; Baker et al. 2020). We contribute to this rapidly growing literature by adopting a different approach to measuring tail risk and systemic risk and a more careful examination of specific large financial institutions.

Figure 1 – Aggregate US financial sector SRISK – MES analysis

Notes: The figure displays the aggregate SRISK levels of the US financial sector generated from the MES analysis, described in section 2.2, in the in the period from January 2019 to July 2020. The shaded area indicates the COVID-19 period, which starts from 21/01/2020 when the first COVID-19 case was identified in the US.

We conduct our analysis mainly based on the CoVaR methodology of Adrian and Brunnermeier (2016). For this purpose, using quantile regressions, we first analyse the Value-at-Risk (VaR) values of the aggregate US financial sector and 18 large financial institutions individually. In the next stage, we estimate the CoVaR and ΔCoVaR values for the sample institutions to see how the COVID-19 crisis has affected the systemic risk of these institutions. As suggested by Ashraf (2020), we use the number of infected cases rather that the fatalities to account for severity of the breakout. In addition to the number of cases, we also study the effect of increases in government stringency that aimed to slow down the spread of the virus. This way, we investigate both the effects of the potential economic shocks and the effects of government response to the shocks. To test for further evidence on the effect of the pandemic on the US financial sector systemic risk, we also run a VAR(1) model using the SRISK index.

Figure 2 – Aggregate US financial sector SRISK – GMES analysis

Notes: The figure displays the aggregate SRISK levels of the US financial sector generated from the GMES analysis, described in section 2.2, in the in the period from January 2019 to July 2020. The shaded area indicates the COVID-19 period, which starts from 21/01/2020 when the first COVID-19 case was identified in the US.

Our results show that the daily number of new COVID-19 cases has had a significantly positive impact on the VaR of the aggregate financial sector. We also document that increases in government stringency have been associated with rises in the aggregate VaR. Furthermore, we find evidence that the positive effect of the VIX on the financial sector VaR has been significantly amplified on the days with new COVID-19 cases. The significant impact of VIX on financial system risk is also documented by Bianconi, Hua, and Tan (2015). When it comes to the individual institutions, our results show that the number of new cases has significantly increased the VaR of all the 18 large financial institutions in our sample. Increased government stringency however has had a mixed effect on the VaR of the institutions.

With regards to systemic risk, we show that the ΔCoVaR and SRISK values of 8 of the largest financial institutions in the US have soared substantially after the identification of the first COVID-19 case in the US (the period we refer to as "COVID-19 period"). This increase is more prominent in the case for ΔCoVaR. All the 8 financial institutions that we examined, have reached record high ΔCoVaR values in the COVID-19 period, since the beginning of 2019. In our regression analysis, we find evidence that increases in the number of COVID-19 cases have positively affected the CoVaR of the financial institutions in 10 out of the 18 sample cases. That is to say, the positive impact of these institutions' losses on the system's VaR has been stronger on the days with new COVID-19 cases. Finally, our SRISK analysis provides some modest evidence that the increases in government stringency have increased the total SRISK levels in US financial system. This suggests that the disruption in the economy caused by the lockdown restrictions have made the financial system more exposed to macroeconomic shocks.

Our results have important policy implications in the road to recovery from the COVID-19 crisis. While policy actions to stimulate economic activity and facilitate lending might be essential in such circumstances, it is important not to overlook financial system stability. With systemic risk at record highs following the COVID-19 crisis, implementing new and innovative macroprudential measures might be necessary to prevent an upcoming system-wide distress. As more data becomes available regarding COVID-19 and the government's response to it, further research on the impact of specific policy actions can provide us with better clues about the best possible strategies to tackle the crisis.

The remainder of this paper is structured as follows: section **2** describes our sample and elaborates on our econometric methodology. Section **3** discusses the results. Section **5** concludes.

2. Data and Methodology

2.1. Sample description

To examine the consequences of the COVID-19 pandemic on the idiosyncratic and systemic risk in the US financial system, we use the daily returns of the 18 largest financial institutions (as of the end date of our sample period) in the US from 01/01/2019 until 22/06/2020 for our CoVaR analysis. The firms are classified as financial institutions according to their Standard Industrial Classification (SIC) codes (from 6000 to 6999). In addition, we analyse the SRISK levels of our sample institutions and the US financial sector from 01/01/2019 until 06/08/2020. Because our preference was to use the most recent data available at the time of conducting the research, the ending dates for the CoVaR and SRISK analyses are not exactly the same. **Table 1** contains summary statistics and brief description of our sample financial institutions. Our sample institutions constitute about 40% of the total market capitalisation of the US financial sector at the end of our sample period. In addition to the firm level returns, we also analyse the daily returns of an equally weighted and a value-weighted index of all US financial firms (SIC codes 6000-6999). The daily stock prices are collected from COMPUSTAT data base and the SRISK values are provided by the NYU Stern Volatility Laboratory.[2]

[2] https://vlab.stern.nyu.edu

Table 1 - Summary description of the sample financial institutions

Entity Name	*Ticker*	*SIC Code*	*SIC Industry Title*	*Obs*	*Mean Return*	*S.D. of Returns*	*Min Return*	*Max Return*	*M. Cap ($bn)*	*Market Share*
BANK OF AMERICA CORP	BAC	6021	National commercial banks	369	0.0010	0.0418	-0.1540	0.2580	213.59	3.44%
JPMORGAN CHASE & CO	JPM	6021	National commercial banks	369	-0.0003	0.0405	-0.1834	0.2680	294.80	4.74%
WELLS FARGO & CO	WFC	6021	National commercial banks	369	-0.0009	0.0456	-0.2660	0.2688	112.13	1.80%
MASTERCARD INC	MA	6099	Functions related to depository banking	370	0.0010	0.0314	-0.1273	0.1661	302.32	4.86%
VISA INC	V	6099	Functions related to depository banking	369	0.0008	0.0272	-0.1355	0.1384	328.92	5.29%
AMERICAN EXPRESS CO	AXP	6141	Personal credit institutions	369	0.0007	0.0516	-0.2650	0.4156	80.05	1.29%
CITIGROUP INC	C	6199	Finance services	369	0.0003	0.0572	-0.3155	0.3887	108.38	1.74%
CME GROUP INC	CME	6200	Security & commodity brokers, dealers, exchanges & services	369	0.0013	0.0278	-0.1839	0.1184	62.78	1.01%
GOLDMAN SACHS GROUP INC	GS	6211	Security brokers, dealers & flotation companies	369	-0.0002	0.0398	-0.1870	0.2338	69.95	1.13%
MORGAN STANLEY	MS	6211	Security brokers, dealers & flotation companies	369	0.0010	0.0542	-0.2276	0.3041	74.65	1.20%
BLACKROCK INC	BLK	6282	Investment advice	369	0.0009	0.0360	-0.1429	0.2328	85.34	1.37%
ANTHEM INC	ANTM	6324	Hospital & medical service plans	369	0.0014	0.0336	-0.1713	0.1562	66.86	1.08%
CIGNA CORP	CI	6324	Hospital & medical service plans	369	0.0008	0.0337	-0.1622	0.1692	70.25	1.13%
UNITEDHEALTH GROUP INC	UNH	6324	Hospital & medical service plans	370	0.0009	0.0271	-0.1728	0.1280	277.56	4.46%
AMERICAN TOWER CORP	AMT	6798	Real estate investment trusts	369	0.0016	0.0310	-0.1516	0.1453	117.30	1.89%
CROWN CASTLE INTL CORP	CCI	6798	Real estate investment trusts	369	0.0017	0.0286	-0.1243	0.1262	69.32	1.12%
EQUINIX INC	EQIX	6798	Real estate investment trusts	369	0.0015	0.0232	-0.1266	0.1160	61.71	0.99%
PROLOGIS INC	PLD	6798	Real estate investment trusts	369	0.0010	0.0302	-0.1727	0.1466	68.36	1.10%

Notes: The table provides details of the financial institutions under study. The column 'Obs' shows the number of observations, 'Mean Return', 'S.D. of Returns', 'Min Return' and 'Max Return' present the mean, standard deviation, minimum and maximum of the firm's daily stock returns during the sample period. 'M.Cap' refers to the market capitalisation of the firm at the end of the sample period (22/06/2020) and 'Market Share' is the ratio of 'M.Cap' to the total US financial sector market capitalisation on the same date.

2.2. Econometric methodology

Our econometric framework is mainly constructed around the two common systemic risk measures: CoVaR and SRISK. In the CoVaR section, we first analyse the impact of COVID-19 pandemic on idiosyncratic tail risk of our sample firms and the aggregate financial sector using VaR estimations. In the next stage, we investigate how the systemic risk of our sample firms has responded to the pandemic by estimating the CoVaR and ΔCoVaR of the firms.

Following the approach of Adrian and Brunnermeier (2016), we use quantile regressions to estimate VaR and CoVaR. Quantile regressions are designed to predict certain quantiles of the response variable, rather than the mean, which is predicted by the traditional OLS estimations. This makes quantile regression a very convenient and efficient method to compute VaR and CoVaR. For the VaR estimations, we regress the daily returns on a set of state variables as in the model below. In addition, we include two COVID-19-related variables: the log of the number of new cases every day[3] (*NC)* and a dummy (*StrInc)* indicating the days new restrictive measures were introduced by the government (i.e., days when the value of the government stringency index has increased). Therefore, our VaR quantile regression can be presented as follows. Similar to Adrian and Brunnermeier (2016) and the common practice, we use the 99%-quantile.

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \theta_q^i VIX_t + \beta_{1,q}^i NC_t + \beta_{2,q}^i StrInc_t + \epsilon_{q,t}^i \quad (1)$$

where X_t^i is the daily loss of the stock or the index *i* (i.e. daily returns × -1) and the subscript *q* refers to the considered quantile. The vector *M* consists of 6 macroeconomic state variables, similar to the model introduced in Adrian and Brunnermeier (2016). These variables are as follows:

i. The change in the 3-month treasury bill rate *(T3Mdiff)*.

[3] The new cases reported on non-trading days are cumulated over the following trading day's number of cases.

ii. The change in the slope of the yield curve, measured by the spread between the 10-year and the 3-month treasury bill rate. *(YCdiff)*

iii. A short-term TED spread, which is defined as the difference between the 3-month LIBOR rate and the 3-month secondary market treasury bill rate. This spread is used a proxy for short-term funding liquidity risk. *(TED)*

iv. Moody's seasoned BAA corporate bond yield relative to the yield on the 10-year treasury bill. *(BAAto10Y)*

v. The daily return on the S&P500 index, used as a market proxy *(S&P500)*.

vi. The daily return of the real estate sector (with SIC codes 65XX and 66XX) in excess of the (value-weighted) financial sector return *(RealEst_ExcRet)*.

The variables related to items (i), (ii), (iii) and (iv) are collected from the St. Louis Fed's FRED data base. With respect to the volatility measure, unlike Adrian and Brunnermeier (2016) who use the lagged historical volatility, we use the contemporaneous log-returns of the CBOE's VIX index to control for the market's volatility state. This makes it possible to draw a comparison between the effects of the current news (i.e. COVID-19 data) and the future expectations, in a framework similar to Bianconi, Hua, and Tan (2015). The daily values of S&P500 index and the VIX are collected from Yahoo! Finance.

The data regarding the COVID-19 pandemic are obtained from the Our World in Data website[4], provided by the University of Oxford and Global Change Data Lab. Since most of the COVID-19-related variables are almost perfectly correlated (e.g. number of deaths, number of cases abroad etc.), we particularly use two variables, the number of daily new cases and the government stringency index from this data source. To overcome the correlation issue between these two variables (also the issue of limited variation in stringency index values), we convert the stringency index into a dummy (*StrInc*), which indicates the days that the stringency index has increased. As documented by Ashraf (2020), the

[4] https://ourworldindata.org

number of new cases are found to have a more significant impact on the stock market than the number of fatalities. Thus, our variables of interest in equation (1) are *NC* and *StrInc.*

The fitted values from equation (1) are equal to the 99% daily VaR of the institution or index *i,* thus the coefficients $\hat{\beta}^{i}_{1,99\%}$ and $\hat{\beta}^{i}_{2,99\%}$indicate the impact of the COVID-19 variables on the estimated VaR, which can be presented as:

$$VaR^{i}_{q,t} = \hat{\alpha}^{i}_{q} + \hat{\gamma}^{i}_{q} M_{t-1} + \theta^{i}_{q} VIX_{t} + \hat{\beta}^{i}_{1,q} NC_{t} + \hat{\beta}^{i}_{2,q} StrInc_{t} \tag{2}$$

where q = 99%.

To further analyse the potential impact of COVID-19 on the financial system VaR, we interact VIX with a dummy representing the days with new COVID-19 cases. This helps us to test if the impact of volatility expectations on the financial system tail risk has changed due to the COVID-19 crisis. The dummy variable we use for this purpose, *NC_dummy,* is equal to 1 on the days with new COVID-19 cases and zero otherwise. Note that from 27/02/2020 onwards there has constantly been new COVID-19 cases announced until the end of our sample period. Hence, *NC_dummy* can also approximately be considered as a dummy controlling for the COVID-19 period in the US. We include this dummy in our model to test whether the COVID-19 period affects our results regardless of the severity of the pandemic (i.e., number of cases). Also, this dummy makes our interaction term easier to interpret. The VaR quantile regression with the interaction term can be presented as:

$$\begin{aligned} X^{i}_{t} = \alpha^{i}_{q} + \gamma^{i}_{q} M_{t-1} + \theta^{i}_{1,q} VIX_{t} + \beta^{i}_{1,q} NC_{t} + \beta^{i}_{2,q} StrInc_{t} + \\ \theta^{i}_{2,q} NC\_dummy_{t} \times VIX^{i}_{t} + \beta^{i}_{5,q} NC\_dummy_{t} + \epsilon^{i}_{q,t} \end{aligned} \tag{3}$$

In the next stage of our analysis, we investigate the impact of the COVID-19 crisis on the CoVaR of our sample banks. As elaborated by Adrian and Brunnermeier (2016), CoVaR measures the q% VaR of the financial system conditional on firm i being in a distress state. So, the CoVaR of institution i can be formulated as:

$$CoVaR_{q,t}^{i} = VaR_{q,t}^{S|X_t^i=VaR_{q,t}^i} \tag{4}$$

where $VaR_{q,t}^{S|X_t^i=VaR_{q,t}^i}$ refers to the q% VaR of the system, when $X_t^i = VaR_{t,q}^i$.

Therefore, the following quantile regression must be estimated to obtain the VaR of the system conditional on stock *i* 's losses:

$$X_t^S = \alpha_q^{S|i} + \gamma_q^{S|i} M_{t-1} + \theta_q^i VIX_t + \beta_{3,q}^{S|i} X_t^i + \epsilon_{q,t}^{S|i} \tag{5}$$

where X_t^S refers to the daily percentage loss of the system (i.e. the value-weighted index of all US financial stocks). Since our purpose is to evaluate the potential effect of the COVID-19 pandemic on the systemic risk of our sample financial institutions, we expand equation (5) as follows:

$$\begin{aligned} X_t^S = \alpha_q^{S|i} + \gamma_Q^{S|i} M_{t-1} + \theta_q^i VIX_t + \beta_{1,q}^{S|i} NC_t + \beta_{2,q}^{S|i} StrInc_t + \\ \beta_{3,q}^{S|i} X_t^i + \beta_{4,q}^{S|i} NC\_dummy_t \times X_t^i + \beta_{5,q}^{S|i} NC\_dummy_t + \epsilon_{q,t}^{S|i} \end{aligned} \tag{6}$$

We interact NC_dummy_t with X_t^i in order to determine whether the slope of X_t^i changes on the days the total COVID-19 cases increase in the US. Similar to the VaR case, we run our CoVaR regressions at the 99% quantile.

To further investigate the impact of COVID-19 crisis on systemic risk, we compute and plot ΔCoVaR for our sample financial institutions. For the sake of brevity, we only present the results for 8 of the sample firms from different subsectors. To obtain a quantifiable measure of a firm's systemic risk, Adrian and Brunnermeier (2016) propose calculating the ΔCoVaR of the firm, defined as:

$$\Delta CoVaR_{q,t}^{i} = CoVaR_{q,t}^{S|X_t^i=VaR_q^i} - CoVaR_{q,t}^{S|X_t^i=VaR_{50}^i} = \hat{\beta}_{3,q}^{S|i}(VaR_{q,t}^i - VaR_{50,t}^i) \tag{7}$$

Therefore, ΔCoVaR measures the difference between the CoVaR of the system when institution *i* is under distress ($X_t^i = VaR_{q,t}^i$) and when the institution is in a median state ($X_t^i = VaR_{50\%,t}^i$). The coefficient $\hat{\beta}_{3,q}^{S|i}$ is obtained by estimating the quantile regression in equation (5). Similar to the previous cases we set q = 99%.

In the final stage of our analysis, we use an alternative measure of systemic risk instead of CoVaR to analyse systemic risk during the COVID-19 crisis. Introduced by Acharya, Engle, and Richardson (2012), SRISK measures the expected capital shortfall of a financial institution, in case of a market-wide crisis. This means that in contrast to CoVaR, the direction of conditioning in SRISK is from system to the firm. Thus, SRISK is defined as:

$$SRISK_{i,t} = E_{t-1}(Capital\ Shortfall_i | Crisis) \tag{8}$$

where "crisis" is defined as a 40% decline in the market proxy over a 6-month time horizon and capital shortfall is estimated based on an 8% prudential capital ratio. Based on this prudential capital ratio, which we denote by *k,* the above formula can be expanded as:

$$\begin{aligned} SRISK_{i,t} &= E\left(\left(k\left(Debt_{i,t} + Equity_{i,t}\right) - Equity_{i,t}\right) \mid Crisis\right) \\ &= kDebt_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right) \times Equity_{i,t} \end{aligned} \tag{9}$$

where LRMES is the Long-run Marginal Expected Shortfall defined as the fractional loss of the institution's equity value conditional on a significant drop in aggregate market in a six-month horizon. Therefore, SRISK shows us how much the equity value of the firm is expected to go below *k%* of its total assets, conditional on a crisis breaking out.

We use two different versions of SRISK provided by the Volatility Laboratory: the SRISK generated from the Marginal Expected Shortfall (MES) analysis (**Figure 1** and **Figure 4**), and the SRISK generated via the Global Marginal Expected Shortfall (GMES) analysis (**Figure 2** and **Figure 5**). MES analysis models a crisis within the US and uses S&P500 as the market index whereas GMES analysis models a worldwide crisis and uses the MSCI All Country World index as the market proxy.[5] Therefore, the former gives us an overview on how sensitive the firms are to a country-wide market distress while the latter shows us the firms' exposure to a global economic turmoil. We run a VAR(1) model with each of the two SRISK measures and VIX as the endogenous variables and *NC* and *StrInc* as the exogenous variables. We chose the number of lags based on the Akaike information criterion (AIC). This analysis allows us to test whether the number of new COVID-19 cases and the government restrictive measures have had impact on the aggregate systemic risk in addition to the effect that is captured via the VIX.

3. Results and discussions

3.1. COVID-19 and idiosyncratic tail risk

Our first set of results analyse the idiosyncratic tail risk of the entire financial system during the COVID-19 period. **Table 2** provides results from the 99% VaR estimations of our equally weighted and value-weighted portfolios of the aggregate financial sector. The first two columns do not include any COVID-19-related variables and show how the state variables' impact the VaR levels. Columns (3) and (4) show the impact of the new COVID-19 cases and government stringency increases on the financial system VaR. In the last two columns, we interact our "new cases dummy" (*NC_dummy)* with VIX to test whether COVID-19 has caused a shift in the effect of VIX on the financial system tail risk.

The results suggest that *NC* has significantly increased the VaR of both our portfolios, in similar magnitudes. However, *StrInc* has had opposite effects on the equally weighted and the value-weighted portfolios. While there seems to be a stabilising impact of the government restrictive measures on the equally weighted portfolio, the value-weighted portfolio has become riskier as a result of the new measures. This suggests that the lockdown measures were perceived more beneficial to the smaller financial institutions while the larger institutions were negatively affected by the new restrictions. The

[5] Additional details on the estimation of SRISK can be found on V-Lab's website: https://vlab.stern.nyu.edu.

results in columns (5) and (6) show that the impact of VIX on the VaR of financial institutions has become significantly more positive during the COVID-19 crisis. Thus, we can argue that increases in the number of COVID-19 cases have made the financial system riskier both directly and by making the stock market more sensitive to the increases in the "fear index".

Table 2 - Financial system VaR estimations

	(1)	(2)	(3)	(4)	(5)	(6)
	VW	**EW**	**VW**	**EW**	**VW**	**EW**
T3Mdiff	-0.08752	0.04700	-0.05510	-0.01704	0.14771	-0.02202
	(2.62)***	(1.55)	(1.80)*	(0.88)	(5.23)***	(1.12)
YCdiff	0.01105	0.04516	0.04445	-0.00430	0.09232	0.00703
	(0.43)	(3.01)***	(2.66)***	(0.43)	(4.52)***	(0.71)
TED	-0.01674	-0.05417	-0.03382	-0.01941	-0.04720	-0.02029
	(0.99)	(8.82)***	(4.77)***	(3.15)***	(7.49)***	(3.51)***
BAAto10Y	0.06440	0.05143	-0.00716	0.00618	0.02600	0.00760
	(14.74)***	(13.21)***	(1.19)	(2.26)**	(4.62)***	(2.68)***
RealEst_ExcRet	0.05461	0.18752	-0.06980	0.00579	-0.02388	0.01498
	(1.54)	(8.23)***	(2.58)**	(0.31)	(0.87)	(0.82)
S&P500	0.01521	0.29690	0.16663	0.11367	-0.00353	0.05340
	(0.13)	(4.34)***	(1.98)**	(1.81)*	(0.04)	(0.92)
VIX	0.10464	-0.02762	0.08067	-0.05366	0.08057	-0.05150
	(11.09)***	(3.23)***	(8.79)***	(9.79)***	(9.38)***	(11.79)***
NC			**0.00879**	**0.00796**	**0.00545**	**0.00887**
			(7.31)***	(8.68)***	(4.14)***	(9.46)***
StrInc			**0.02187**	**-0.02234**	**0.01728**	**-0.00629**
			(2.54)**	(3.85)***	(1.65)*	(1.10)
*VIX * NC_dummy*					**0.17890**	**0.07404**
					(4.92)***	(2.16)**
NC_dummy					-0.00575	-0.01462
					(1.21)	(6.22)***
_cons	-0.10107	-0.08080	0.05526	-0.00190	-0.01379	-0.00506
	(8.68)***	(10.84)***	(4.16)***	(0.31)	(1.11)	(0.81)
Obs	*348*	*348*	*348*	*348*	*348*	*348*

*Notes: The table presents the quantile regression results that estimate the 99% daily VaR of the aggregate US financial sector, represented by a value-weighted (VW) and an equally weighted (EW) portfolio. The variables and the estimated model are explained in section 2. The numbers in parentheses represent the t-statistics obtained from heteroskedasticity-robust standard errors estimated via an Epanechnikov kernel function (Koenker 2005). The sample period covers trading days from 01/01/2019 to 22/06/20202. * p<0.1; ** p<0.05; *** p<0.01.*

In the next stage of our analysis, we examine the impact of COVID-19 on the VaR of 18 large financial institutions individually. As the results in **Table 3** indicate, *NC* has significantly increased the estimated VaR of all our sample firms, with Citigroup being the most heavily affected. With regards to *StrInc* however, the effect has not been as homogenous. Within our sample, 9 financial institutions, including medical insurance providers Anthem, Cigna and Unitedhealth Group, have had significantly higher VaRs as a result of the increased government stringency.

The counterintuitive reaction of medical insurance providers to the lockdown measures can be due to two possible reasons. First, the lockdown announcements can be perceived by the market as alarming and negative signals from the government about the upcoming exacerbation of the pandemic. Hence, it is plausible for medical insurance companies to become riskier under such conditions. Second, the lockdown measures forced business shutdowns which led to substantial rises in the unemployment rate. A rise in unemployment has been shown to be associated with reductions in health insurance coverage among adults (Cawley, Moriya, and Simon 2015), which can in turn negatively affect medical insurance providers. Nevertheless, *StrInc* has caused a significant reduction in the VaR levels of 5 of the sample institutions, meaning their tail risk has been mitigated as a result of the lockdown measures. Overall, it is evident that *StrInc* has not had a consistent effect on the tail risk of the financial institutions and the reactions have clearly been idiosyncratic.

Comparing the estimated coefficients of VIX and *NC* in **Table 3** suggests that although the economic impact of VIX on the financial institutions' VaRs is larger, the *NC* coefficient has been statistically significant in more cases. This implies that the tail risk in the stock markets is driven by both current news and the future volatility expectations. This finding is somewhat contrary to those of Bianconi, Hua, and Tan (2015), who show that, in comparison to future expectations, the real-time printed-word information has limited direct effect on distress within financial intuitions.

Table 3 – Top 18 financial institutions VaR estimations

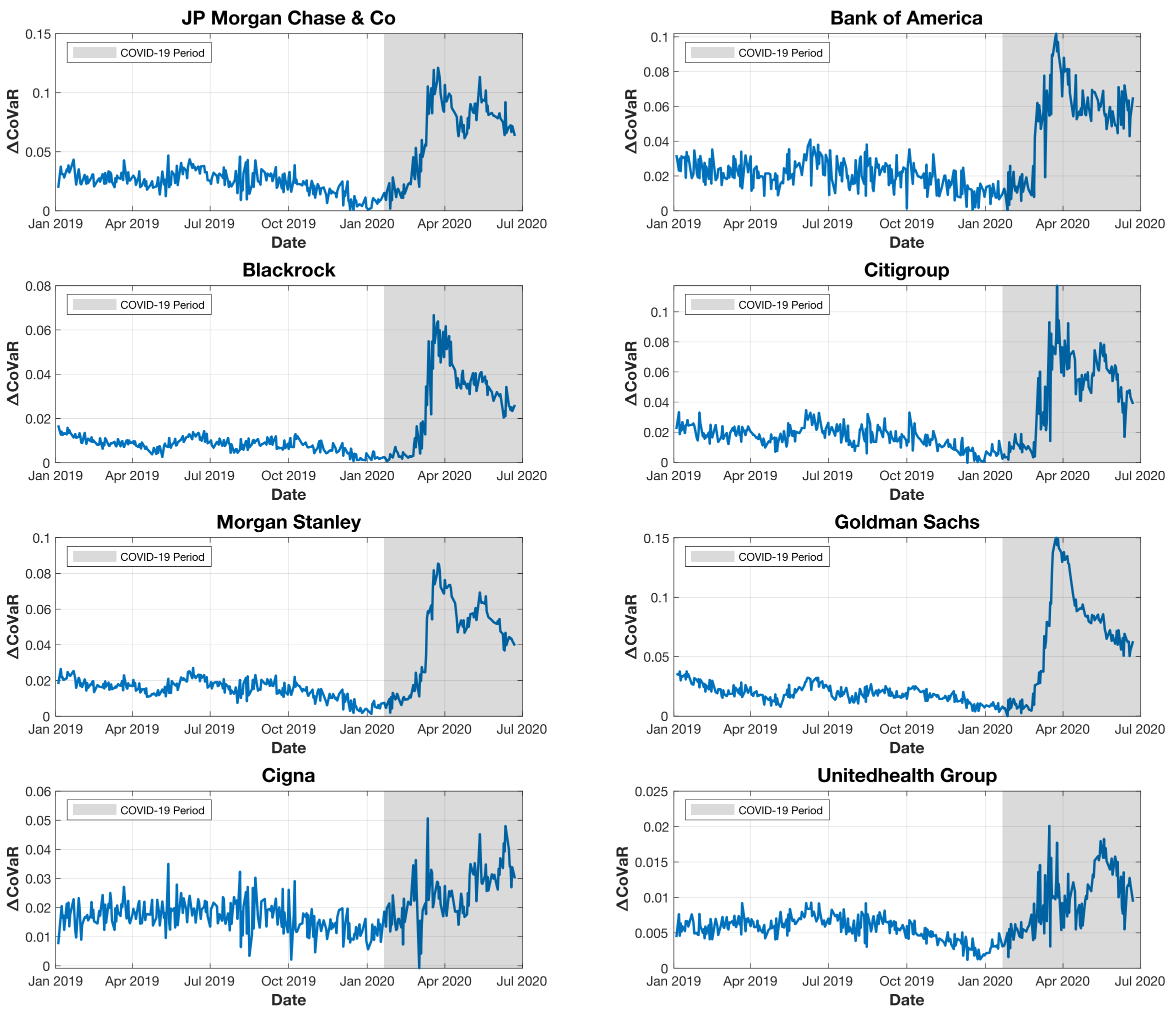
	AXP	AMT	ANTM	BAC	BLK	CI	CME	C	CCI	EQIX	GS	JPM	MA	MS	PLD	UNH	V	WFC
T3Mdiff	0.05914	0.06050	0.11413	-0.15698	0.08095	-0.07765	0.00695	0.08772	-0.05988	-0.05032	0.12212	-0.09752	0.14832	0.10952	-0.01079	0.21776	0.04338	0.18507
	(2.03)**	(1.61)	(2.25)**	(4.09)***	(2.75)***	(1.61)	(0.15)	(1.77)*	(1.45)	(1.44)	(3.13)***	(2.68)***	(5.66)***	(2.80)***	(0.28)	(5.23)***	(1.49)	(3.80)***
YCdiff	0.03128	0.05110	0.10235	-0.01054	0.03952	0.01027	0.23916	0.06311	-0.03442	-0.04130	0.01679	0.01495	0.03067	0.07735	0.05251	0.06030	0.04625	0.04875
	(1.33)	(2.48)**	(3.62)***	(0.39)	(1.70)*	(0.38)	(9.08)***	(1.73)*	(1.76)*	(1.90)*	(0.63)	(0.73)	(1.77)*	(2.67)***	(2.14)**	(2.33)**	(2.56)**	(1.60)
TED	-0.06457	-0.06110	0.00206	-0.07365	-0.02880	-0.05611	-0.01693	-0.14535	-0.04933	0.01893	-0.12840	-0.08181	-0.06542	-0.12533	-0.02816	-0.03978	-0.04162	-0.12909
	(3.66)***	(7.40)***	(0.23)	(5.22)***	(1.93)*	(5.41)***	(2.15)**	(7.01)***	(6.34)***	(2.09)**	(8.61)***	(8.20)***	(7.02)***	(10.02)***	(2.78)***	(4.12)***	(4.91)***	(7.77)***
BAAto10Y	-0.00194	0.04444	-0.02491	0.01100	0.02629	-0.00532	0.01321	0.00577	0.01374	0.00839	0.01756	-0.02199	0.03697	0.04170	-0.01885	0.02773	0.00021	0.01082
	(0.18)	(6.52)***	(2.79)***	(1.25)	(3.49)***	(0.66)	(1.83)*	(0.45)	(2.06)**	(1.20)	(1.77)*	(2.74)***	(5.64)***	(4.22)***	(2.33)**	(3.75)***	(0.04)	(0.95)
RealEst_ExcRet	-0.08698	-0.15734	-0.39804	-0.07415	0.14825	-0.04715	0.07019	-0.18175	-0.29082	0.05748	-0.08847	0.03699	-0.13849	-0.17078	-0.05352	-0.36371	-0.12520	0.10650
	(2.24)**	(4.66)***	(8.91)***	(1.78)*	(4.45)***	(1.18)	(2.10)**	(3.21)***	(8.98)***	(2.04)**	(2.00)**	(1.00)	(3.83)***	(3.62)***	(1.60)	(8.51)***	(4.52)***	(1.95)*
S&P500	-0.24021	0.16361	0.28531	0.11707	-0.25291	0.22049	-0.02870	0.06799	-0.08603	-0.08602	0.30402	0.26103	0.05533	-0.27684	-0.22769	0.18514	0.03574	0.48828
	(2.13)**	(1.72)*	(2.79)***	(0.89)	(1.82)*	(1.90)*	(0.26)	(0.49)	(0.92)	(0.78)	(2.76)***	(2.50)**	(0.83)	(1.90)*	(1.05)	(1.83)*	(0.40)	(3.06)***
VIX	0.13447	0.08701	-0.01930	0.10744	0.11067	0.04408	0.01310	0.09103	0.08572	0.13633	0.10006	0.06281	0.18894	0.07162	0.10610	0.08694	0.07573	0.13963
	(10.02)***	(7.23)***	(1.32)	(7.95)***	(11.03)***	(3.18)***	(1.15)	(4.77)***	(6.91)***	(10.91)***	(6.72)***	(5.34)***	(15.76)***	(5.12)***	(9.24)***	(6.65)***	(8.21)***	(7.83)***
NC	**0.02298**	**0.00238**	**0.00627**	**0.01336**	**0.00865**	**0.00805**	**0.00313**	**0.02610**	**0.00452**	**0.00326**	**0.01599**	**0.01842**	**0.00572**	**0.01304**	**0.01180**	**0.00247**	**0.00854**	**0.01940**
	(4.35)***	(2.54)**	(6.15)***	(5.61)***	(5.79)***	(6.47)***	(3.67)***	(6.27)***	(4.88)***	(3.98)***	(5.78)***	(9.75)***	(4.16)***	(7.19)***	(7.25)***	(2.74)***	(6.82)***	(6.35)***
StrInc	**-0.06881**	**0.01574**	**0.05937**	**-0.02351**	**0.01885**	**0.04561**	**0.09281**	**-0.04702**	**0.02066**	**0.02227**	**-0.01374**	**-0.01548**	**-0.03960**	**0.00370**	**0.06415**	**0.03571**	**0.02259**	**-0.00657**
	(3.35)***	(1.74)*	(3.91)***	(2.32)**	(1.43)	(3.52)***	(5.55)***	(3.21)***	(2.36)**	(1.70)*	(1.38)	(1.78)*	(7.25)***	(0.34)	(1.95)*	(3.10)***	(2.23)**	(0.55)
_cons	0.04408	-0.04737	0.10786	0.02320	-0.03132	0.06282	0.00744	0.05739	0.02018	0.00368	0.02572	0.09266	-0.03139	-0.02298	0.07081	-0.00572	0.03341	0.04416
	(1.71)*	(3.21)***	(5.69)***	(1.15)	(1.75)*	(3.62)***	(0.48)	(1.90)*	(1.40)	(0.24)	(1.11)	(5.17)***	(2.17)**	(1.05)	(3.82)***	(0.37)	(2.56)**	(1.68)*
Obs	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*349*	*348*	*348*	*349*	*348*	*348*

*Notes: The table presents the quantile regression results that estimate the 99% daily VaR of the 18 largest US financial institutions. . The variables and the estimated model are explained in section 2. Each column is labelled by the corresponding company's stock ticker, as shown in **Table 1**. The numbers in parentheses represent the t-statistics obtained from heteroskedasticity-robust standard errors estimated via an Epanechnikov kernel function (Koenker 2005). The sample period covers trading days from 01/01/2019 to 22/06/20202. * p<0.1; ** p<0.05; *** p<0.01.*

3.2. COVID-19 and systemic risk

In this section we investigate how the COVID-19 crisis has affected the systemic risk of our sample financial institutions using the CoVaR and SRISK approaches. The graphs in **Figure 3** show substantial rises in the estimated ΔCoVaR values during the COVID-19 period for the sample financial institutions, where the biggest jumps have occurred around mid-March.

Figure 3 – Estimated ΔCoVaR time-series plots for 8 large financial institutions

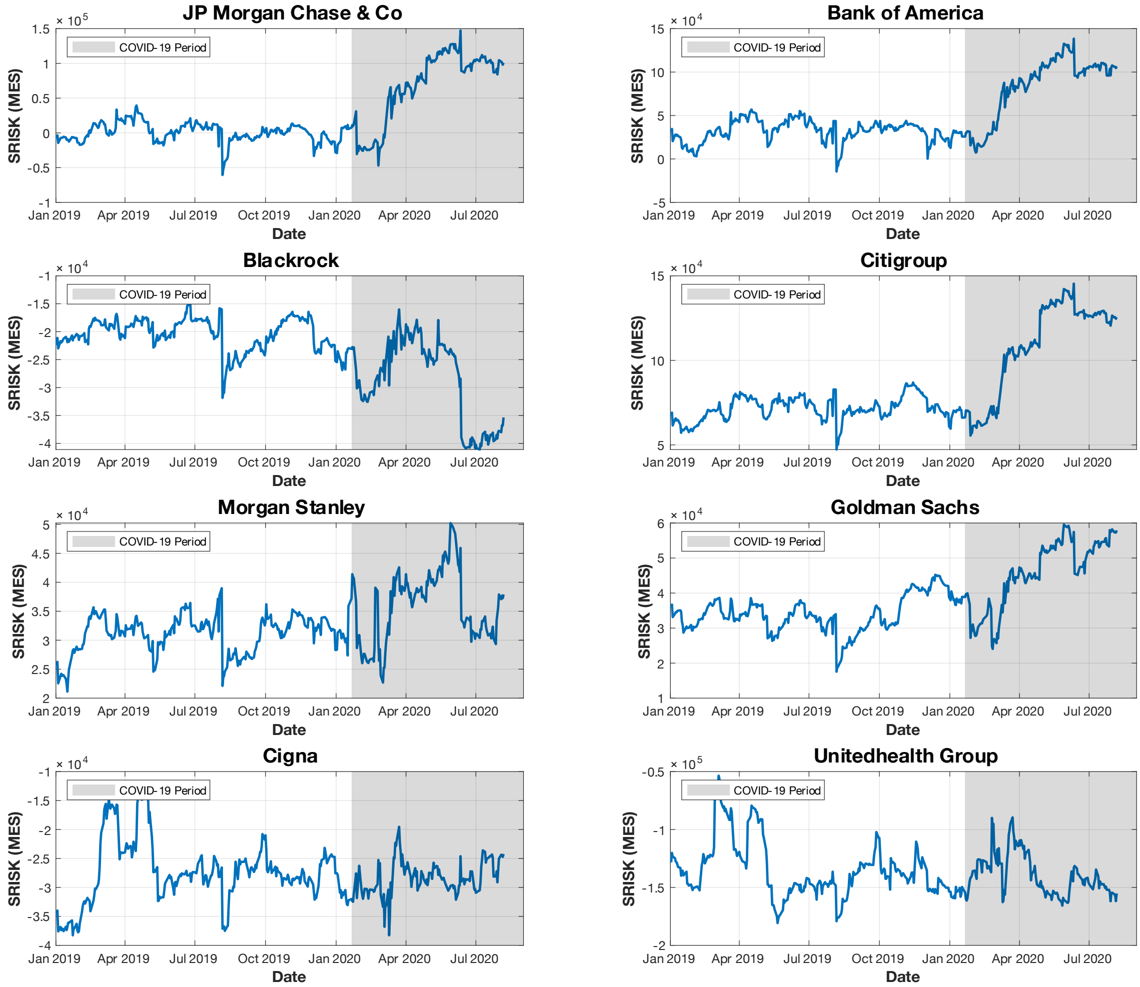


Notes: The time-series plots present the estimated 99% ΔCoVaR values for 8 of our sample financial institutions, based on the methodology explained in section 2.2, and for the period from January 2019 to July 2020.. The shaded areas indicate the COVID-19 period, which starts from 21/01/2020 when the first COVID-19 case was identified in the US.

Comparing across the institutions, the systemic risk contribution of the two large health insurance providers, Cigna Corp. and Unitedhealth Group seem to be relatively less affected by the crisis. This could be because of the higher correlation of the other financial institutions with the financial system, compared to the health insurance companies, due to the nature of their business operations.

The SRISK graphs of the institutions however do not exhibit such prominent rises in systemic risk in every case. This is while the aggregate US SRISK levels from both MES and GMES analyses have increased sharply in COVID-19 period (**Figure 1**). As shown in **Figure 4** and **Figure 5** commercial and investment banks such as JP Morgan Chase & Co. and Bank of America have seen the highest rises in SRISK values, while others show mixed responses.

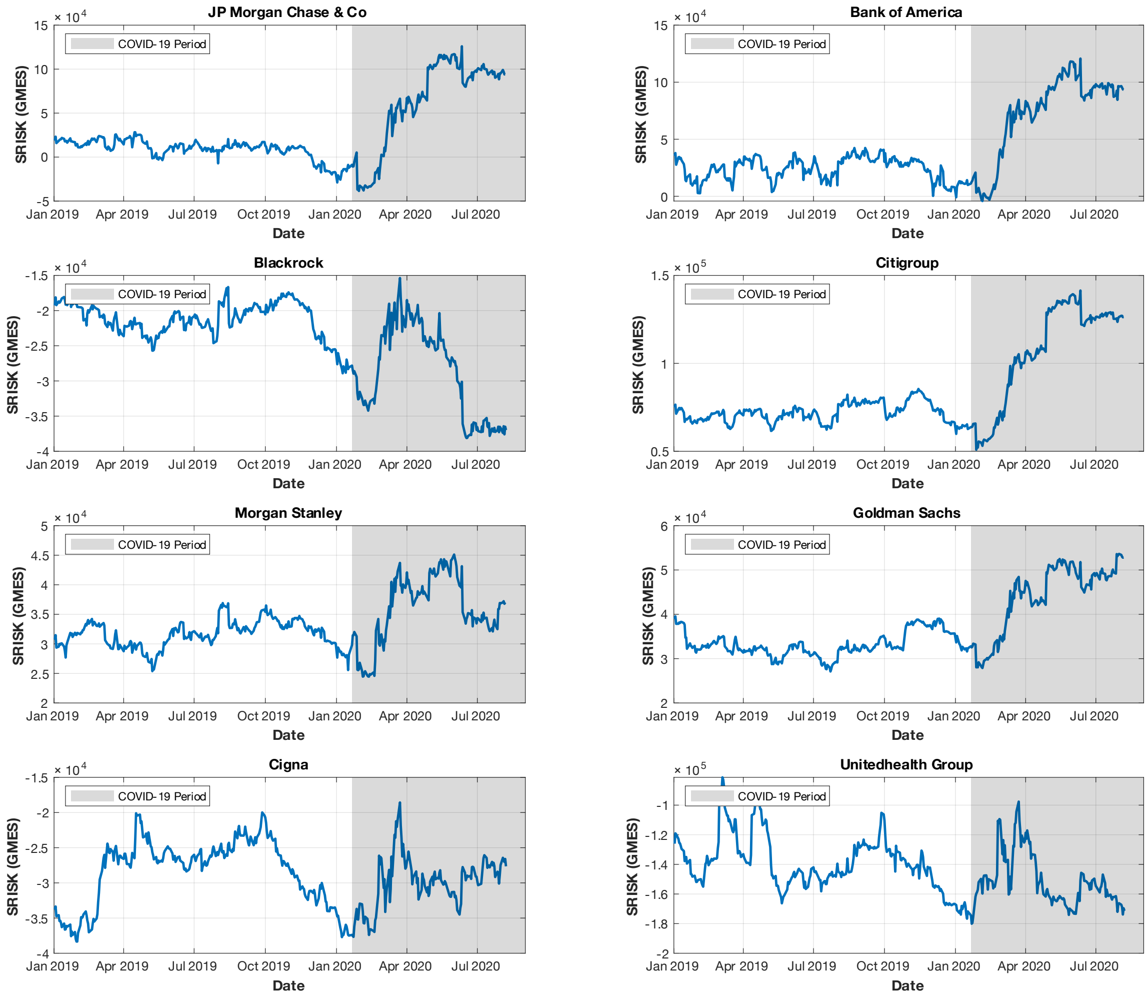
Figure 4 – SRISK (MES) time-series plots for 8 large financial institutions



Notes: Notes: The time-series plots present the SRISK values generated from MES analysis for 8 of our sample financial institutions, based on the methodology explained in section 2.2, and for the period from January 2019 to July 2020. The shaded areas indicate the COVID-19 period, which starts from 21/01/2020 when the first COVID-19 case was identified in the US. Data provided by the NYU Stern Volatility Laboratory.

The SRISK values generated from the GMES analysis display relatively sharper increases, suggesting that COVID-19 pandemic might have made the institutions more susceptible to global economic shocks. Overall, both the ΔCoVaR and SRISK measures indicate substantial rises in US financial sector systemic risk in the wake of the COVID-19 crisis. This implies that the probability of a financial crisis has substantially increased in the post-COVID-19 period and the economic policy responses that can contribute to this risk might prove too costly in the long run.

Figure 5 – SRISK (GMES) time-series plots for 8 large financial institutions



Notes: Notes: The time-series plots present the SRISK values generated from GMES analysis for 8 of our sample financial institutions, based on the methodology explained in section 2.2, and for the period from January 2019 to July 2020. The shaded areas indicate the COVID-19 period, which starts from 21/01/2020 when the first COVID-19 case was identified in the US. Data provided by the NYU Stern Volatility Laboratory.

We run regressions based on both CoVaR and SRISK to further analyse the impact of COVID-19 on the financial sector systemic risk. In doing so, we investigate whether factors directly related to the

COVID-19 crisis (i.e., new cases and lockdown measures) have had an impact on the institutions' systemic risk. This indeed would be in addition to the indirect impact of various economic and social factors, which drive part of the movements demonstrated in the graphs above.

Table 4 reports the results from estimating the CoVaR model as specified in equation (6) for each of the 18 sample institutions. The interaction term, X^i**NC_dummy,*** determines whether the impact of firm *i*'s losses on the system's tail risk has changed due to the increases in COVID-19 cases. As the results indicate, in 10 out of the 18 cases, X^i and X^i**NC_dummy* combined have a statistically significant effect on the system's VaR. This suggests that the COVID-19 crisis has resulted in a substantial increase in systemic risk contribution of these institutions, leading to higher US financial system fragility. The economic scale of this impact has been the largest for Visa Inc., Cigna Corp. and Wells Fargo & Co. according to the estimations.

When comparing the results related to systemic risk with those related to idiosyncratic risk (VaR estimations), we observe that unlike idiosyncratic risk, the response of the institutions' systemic risk to COVID-19 has been relatively heterogenous. While the number of new cases has increased the VaR of all our sample institutions, it has had a mixed effect on the systemic risk contribution of the firms. This could be due to the more complex nature of systemic risk. Although the idiosyncratic stability of a financial institution can have an important effect on its systemic risk, other factors such as size, correlation with the aggregate market and implicit government guarantees also play a fundamental role.

Table 4 – Top 18 financial institutions CoVaR estimations

	AXP	AMT	ANTM	BAC	BLK	CI	CME	C	CCI	EQIX	GS	JPM	MA	MS	PLD	UNH	V	WFC
T3Mdiff	-0.02453	0.09537	-0.00314	0.09020	-0.02706	-0.00144	-0.07915	-0.03353	0.10576	0.11976	0.02698	0.07246	0.12055	-0.00059	0.06841	0.02624	0.09695	0.03924
	(1.07)	(4.35)***	(0.14)	(3.99)***	(0.96)	(0.07)	(3.37)***	(1.25)	(4.83)***	(5.40)***	(1.28)	(2.86)***	(4.60)***	(0.02)	(2.33)**	(1.27)	(4.69)***	(1.15)
YCdiff	0.01449	0.06950	0.02964	0.09777	0.09401	0.01166	0.01354	0.04909	0.06696	0.10576	-0.00410	0.06391	0.09102	0.03273	0.06202	0.04779	0.04660	0.09528
	(1.12)	(4.23)***	(1.81)*	(6.61)***	(5.97)***	(0.83)	(0.88)	(3.41)***	(4.08)***	(6.16)***	(0.33)	(4.21)***	(4.82)***	(2.41)**	(3.45)***	(2.83)***	(3.39)***	(5.04)***
TED	-0.04703	-0.08064	-0.06308	-0.04970	-0.02735	-0.05258	-0.04411	-0.02675	-0.07494	-0.05442	-0.03232	-0.05224	-0.05177	-0.03087	-0.05478	-0.03198	-0.07343	-0.06023
	(6.81)***	(8.05)***	(5.93)***	(9.60)***	(4.97)***	(7.27)***	(7.29)***	(5.32)***	(5.29)***	(6.70)***	(6.05)***	(6.28)***	(8.97)***	(5.08)***	(6.52)***	(3.14)***	(6.70)***	(5.31)***
BAAto10Y	0.00359	0.00568	-0.00285	0.01754	-0.00316	0.00148	0.02114	0.00891	0.00981	0.01738	0.01515	0.02144	0.01022	0.00547	0.01709	-0.00086	0.00701	0.00363
	(0.70)	(0.86)	(0.39)	(3.87)***	(0.64)	(0.25)	(3.49)***	(1.96)*	(1.52)	(2.78)***	(3.50)***	(4.63)***	(2.29)**	(1.16)	(2.82)***	(0.12)	(1.27)	(0.61)
RealEst_ExcRet	-0.09049	-0.02860	-0.07419	-0.03827	-0.14303	-0.04540	0.01746	-0.08676	-0.02534	-0.03486	-0.08267	-0.02462	-0.07392	-0.08791	-0.04427	-0.05131	-0.04444	-0.07968
	(4.08)***	(0.98)	(2.69)***	(1.72)*	(6.03)***	(1.63)	(0.58)	(3.86)***	(0.87)	(1.22)	(3.70)***	(1.03)	(2.83)***	(4.08)***	(1.73)*	(1.93)*	(1.55)	(2.88)***
S&P500	0.11526	-0.03089	-0.03607	0.11180	-0.11036	0.10808	0.20561	0.03683	-0.01721	-0.01987	0.23203	0.16226	-0.01096	0.01905	0.07788	0.12173	-0.00242	0.11798
	(1.98)**	(0.46)	(0.46)	(2.11)**	(1.83)*	(1.64)	(3.31)***	(0.59)	(0.28)	(0.30)	(5.02)***	(2.51)**	(0.15)	(0.33)	(0.77)	(1.68)*	(0.04)	(1.42)
VIX	0.02708	0.07410	0.08014	0.02772	0.03676	0.03886	0.05732	0.02320	0.07500	0.07967	0.00879	0.03650	0.06794	0.05226	0.07658	0.06153	0.04933	0.03428
	(2.71)***	(7.58)***	(7.86)***	(2.92)***	(3.27)***	(3.82)***	(6.51)***	(2.47)**	(7.28)***	(8.05)***	(0.93)	(3.14)***	(6.07)***	(5.82)***	(7.14)***	(6.43)***	(4.13)***	(3.16)***
NC	0.00613	0.01042	0.01152	0.00394	0.00501	0.00710	0.00459	0.00337	0.00913	0.00671	0.00345	0.00366	0.00437	0.00441	0.00574	0.00968	0.00797	0.00889
	(4.53)***	(4.71)***	(4.69)***	(4.06)***	(4.47)***	(4.33)***	(3.36)***	(4.00)***	(3.34)***	(3.70)***	(4.03)***	(2.87)***	(4.18)***	(3.61)***	(3.36)***	(5.00)***	(3.84)***	(4.38)***
StrInc	0.00367	-0.01526	-0.00343	0.00899	0.00590	-0.03391	-0.01298	0.01501	-0.02151	-0.00422	0.01022	0.01385	0.02348	0.00691	0.02997	-0.02588	-0.01486	0.01406
	(0.72)	(3.14)***	(0.49)	(1.91)*	(0.90)	(6.45)***	(2.55)**	(2.32)**	(4.15)***	(0.85)	(2.20)**	(2.32)**	(2.22)**	(1.07)	(1.96)*	(4.89)***	(3.28)***	(1.31)
X^i	**0.38685**	**0.00286**	**0.10461**	**0.23345**	**0.42142**	**0.20482**	**0.32372**	**0.35916**	**0.00740**	**-0.06097**	**0.40675**	**0.22038**	**0.03163**	**0.25200**	**0.23684**	**0.27094**	**0.24547**	**0.25624**
	(5.80)***	(0.05)	(3.09)***	(4.96)***	(6.66)***	(5.82)***	(5.73)***	(7.83)***	(0.13)	(1.23)	(9.12)***	(3.54)***	(0.52)	(5.93)***	(3.63)***	(7.04)***	(3.48)***	(4.71)***
X^i * NC_dummy	**0.06331**	**0.49688**	**0.10699**	**0.24369**	**0.01629**	**0.40937**	**0.12184**	**-0.07683**	**0.53232**	**0.78794**	**0.23992**	**0.24974**	**0.60477**	**0.12889**	**0.18678**	**0.26029**	**0.42504**	**0.28668**
	(0.95)	(5.75)***	(1.39)	(4.20)***	(0.23)	(5.84)***	(1.76)*	(1.41)	(6.48)***	(8.90)***	(4.58)***	(3.27)***	(8.53)***	(2.34)**	(1.80)*	(3.45)***	(5.52)***	(2.91)***
NC_dummy	-0.00967	-0.01201	-0.01712	-0.00946	0.00016	0.00752	-0.00300	-0.00371	-0.01128	-0.00783	-0.00971	-0.00742	-0.00318	-0.00442	-0.00553	-0.00771	-0.01024	-0.01134
	(2.49)**	(2.31)**	(3.29)***	(2.79)***	(0.04)	(1.48)	(0.69)	(1.10)	(1.90)*	(1.61)	(2.87)***	(1.92)*	(0.83)	(1.13)	(1.24)	(1.53)	(2.05)**	(2.22)**
_cons	0.03578	0.04005	0.05485	0.00422	0.04664	0.04007	-0.00594	0.01726	0.02937	0.00717	0.00463	-0.00361	0.02287	0.02632	0.00615	0.03917	0.03433	0.03712
	(3.05)***	(2.56)**	(3.08)***	(0.42)	(4.29)***	(2.95)***	(0.44)	(1.71)*	(1.79)*	(0.49)	(0.48)	(0.34)	(2.34)**	(2.44)**	(0.44)	(2.33)**	(2.57)**	(2.59)**
Obs.	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*348*	*349*	*348*	*348*	*349*	*348*	*348*

*Notes: The table presents the quantile regression results that estimate the 99% daily CoVaR of the 18 largest US financial institutions. The dependant variable in all the column is the daily losses of the value-weighted aggregate portfolio. The columns are labelled with the relevant institution's stock ticker (as in **Table 1**), whose daily loses are included in the model as* $\boldsymbol{X^i}$ *(see section 2.2 for model details). The numbers in parentheses represent the t-statistics obtained from heteroskedasticity-robust standard errors estimated via an Epanechnikov kernel function (Koenker 2005). The sample period covers trading days from 01/01/2019 to 22/06/20202. * p<0.1; ** p<0.05; *** p<0.01.*

To gain a better and more comprehensive view of the systemic risk consequences of the COVID-19 crisis, we test the effect of the pandemic on SRISK, which measures systemic risk via a different approach to CoVaR. **Table 5** presents the results from our VAR(1) model with SRISK and VIX as endogenous and *NC* and *StrInc* as exogenous variables. The top panel reports the results for the SRISK equation (MES or GMES), and the bottom panel summarises the results for the VIX equation.

Table 5 – COVID-19 and the aggregate US SRISK: VAR(1) estimations

		MES	***GMES***
SRISK	*l.SRISK*	0.01594	-0.12336
		(0.33)	(2.39)**
	l.VIX	-0.37420	-0.17622
		(9.52)***	(5.86)***
	NC	**-0.00013**	**0.00007**
		(0.18)	(0.13)
	StrInc	**0.03098**	**0.03289**
		(1.44)	(2.07)**
	_cons	0.00213	0.00119
		(0.57)	(0.44)
VIX	*l.SRISK*	0.10017	0.01241
		(1.58)	(0.13)
	l.VIX	-0.19180	-0.16540
		(3.68)***	(3.04)***
	NC	**-0.00119**	**-0.00115**
		(1.27)	(1.22)
	StrInc	**0.07085**	**0.07237**
		(2.48)**	(2.52)**
	_cons	0.00133	0.00141
		(0.27)	(0.29)
Obs.		*402*	*402*

Notes: The table presents the results from VAR(1) estimations with SRISK and VIX as endogenous and NC and StrInc as exogenous variables. The top panel shows the estimated parameters of the SRISK equation and the bottom panel displays the estimated parameters of the VIX equation. The columns MES and GMES refer to the each of the two variations of SRISK explained in section 2.2. The prefix l. before the variable names denotes the first lag of the variable. The numbers in the parenthesis are the estimated Z statistics. The sample period covers the trading days from 01/01/2019 to 06/08/2020.

Based on these results, the total US SRISK levels have not been significantly affected by the number of new COVID-19 cases announced. This contrasts with most of our previous findings regarding CoVaR analysis. However, there is some evidence that the increases in government restrictive measures (*StrInc*) have caused a significant rise in the GMES SRISK. This suggests that the lockdown policies have made the US financial institutions more exposed to global stock market downturns. The results for the VIX equation also confirm that *StrInc* has significantly increased volatility expectations in the US stock market. Overall, although our findings about the effect of the lockdown measures are not conclusive, the evidence is more suggestive of the negative effect of these measures on financial stability.

Overall, the results from our VAR(1) model suggest that the number of new COVID-19 cases has not had a significant effect on the aggregate SRISK, in excess of the effect that is captured by the VIX. This is slightly in contradiction of our VaR analysis presented in **Table 2**, where we show that the VIX and the number of new COVID-19 cases have both had an impact on the financial system VaR.

4. Study limitations and further research

In this study, our aim was to provide an initial assessment of the detrimental financial consequences of the COVID-19 pandemic. While the pandemic is indisputably the most challenging issue the global economy is facing right now, a true assessment of the situation at this stage is difficult due to the lack of data and previous research on similar topics. Although we tried to use the most recent available data and borrow from the latest research, our study is still an initial stepping stone in this line of research. The literature on this topic needs to expand substantially to address all the important issues.

One potential area that can be further explored in continuation of our study, is an examination of the governments' economic responses to the pandemic, rather than the public health responses, which were analysed in this study. The unprecedented policy actions and economic conditions in this period can lead to unknown economic consequences that need to be studied thoroughly. A second potential area for further research can focus on the firm-specific characteristic of financial institutions to test whether the heterogeneity of responses that were observed in some cases this study could be explained by these characteristics.

5. Concluding remarks

On top of its social and humanitarian costs, the COVID-19 pandemic has caused an unprecedented damage to the economy that is likely to last for several years. There are two main aspects of the crisis which can affect the economy and the financial system separately through different channels. These two aspects are the factors related to the spread and severity of the pandemic and the factors related to the economic policy actions in this period. Our focus in this study is the first aspect.

Specifically, in this study we investigate the consequences of the COVID-19 pandemic on the systemic and idiosyncratic tail risk of the large financial institutions in the US. We find evidence that rises in the number of COVID-19 patients have significantly increased the systemic and idiosyncratic risk within the US financial sector. Furthermore, we show that the ΔCoVaR values of the institutions we examine, have reached record highs after the breakout of the virus in the US. This means that the systemic risk contribution of these institutions has remarkably increased in the COVID-19 period. Our results also suggest that tighter government lockdown policies have been associated with increases in the systemic and idiosyncratic tail risk in the financial system, although the evidence in this regard remain mixed.

These findings call attention to the importance of scrutinising financial system stability while implementing expansionary measures to tackle the COVID-19 crisis. Our findings show that the US financial system is now highly exposed to systemic shocks and failure of a few large financial institutions can trigger a domino of failures within the financial system. With the current record high budget deficit, it would be drastically costly to bailout financial institutions. Hence, precautionary measures to avoid the need for such bailouts seem highly necessary.

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