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Abstract

This doctoral thesis consists of four independent research papers. All papers are empirical and cover the area of financial market risk, with a particular focus on systemic risk and volatility in financial markets.

The first paper analyzes the joint effect of *centrality* and other characteristics that are essential in determining banks' systemic importance. Specifically, we treat centrality as a moderator variable and analyze whether characteristics such as *size* and *Value-at-Risk* become more, or less, important in determining a bank's contribution to systemic risk. Our main finding is that a bank's contribution to systemic risk, measured by $\Delta CoVaR$, given a certain level of *VaR*, is about four times higher for a bank with two standard deviations above average estimated centrality, compared to a bank with average centrality. Neglecting this indirect moderation effect severely underestimates the importance of centrality for "risky" banks and overestimates it for "safer" banks.

The second paper considers the relationship between the concept of *implicit government guarantees* and bank equity returns. In alignment with the risk-return trade off, riskier firms should earn higher expected returns. However, risky financial institutions also pose a threat to financial stability and can be considered '*too big to fail*'. From this perspective it can be argued that the risk-adjusted expected return should be lower for highly systemic financial institutions than for less systemic institutions. The paper examines this conjecture from an asset pricing perspective by sorting bank stocks according to the systemic risk measures $\Delta CoVaR$ and *MES*, and compares their risk-adjusted returns. No clear evidence is found that points towards the perception that implicit government guarantees incurred lower risk-adjusted returns during the period 1987-2013 for highly systemic bank holding companies.

The third paper investigates the relationship between equity volatility and financial leverage on the firm level. We use a comprehensive dataset of large syndicated loans with a total loan amount in excess of USD12tn. This allows us to identify precisely when a company experiences a large change in leverage. In contrast to several previous studies that have relied only on accounting data, we find very clear results that increased financial leverage increases equity volatility. Our findings are robust to controlling for time trends in variance as well as the type and purpose of the loan.

The fourth paper considers volatility dynamics in the *Bitcoin* market. Bitcoin is the world's largest cryptocurrency by market capitalization. Bitcoin is also considered extremely volatile and predicting the volatility of any currency or asset is one of the most fundamental tasks for anyone dealing with investment decisions and risk. We study Bitcoin volatility by looking at the link between the volatility in the Bitcoin market and the volatility in other related traditional markets, as well as the general risk level in the financial system. We also consider retail investor driven search volumes on Google, as a possible proxy for investor sentiment. Our main finding is that there is a relatively strong positive link between Bitcoin volatility and search pressures on Bitcoin-related words on Google, particularly for the search word "bitcoin". Overall, our results point at retail investors, rather than large institutional investors, being major drivers of Bitcoin volatility dynamics.

Key words systemic risk, network, volatility, centrality, implicit guarantees, VaR, leverage, Bitcoin

Classification system and/or index terms (if any) JEL codes: G01, G10, G12, G14, G18, G21, G32, D80, C80

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To my parents

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"It does not do to dwell on dreams and forget to live, remember that"
Professor ALBUS DUMBLEDORE
J.K. Rowling, Harry Potter and the Philosopher's Stone

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[1] 'Always' is an underestimation.

Kaveh, Anne-Marie, Björn, Hjördis, Sara, Anna, Birger, Vinh, Hong, Hassan, Bujar, Dominice, Zahra, Chelsea, Claes, Olga, Veronika and Valeriia. Thank you for being wonderful colleagues and for sharing your wisdom in finance and economics. You have great minds and you have inspired me every day. Additionally, I want to thank all of my fellow PhD comrades through the years that kept the social (and mental) flame alive even in the darkest (of darkest!) of times. This journey has been wonderful in the sense that it was shared with all of you, together at EC1.

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The grass **is** greener on the other side.

Dominika
Stockholm, January 2021

[2] The usual disclaimer applies; the opinions in this doctoral thesis are those of the author(s) and are not necessarily shared by the Riksbank.

Introduction

Why do we study risk and volatility in financial markets? Financial markets channel funds from those who have more than they need, to those who need more than they have. In normal times, this essential credit supply mechanism generally runs smoothly, as the prices of different assets, such as stocks or bonds, reflect all information presently available together with current expectations of what is likely to happen in the future. However, when there is a *crisis* there is often also a lot of uncertainty about what the future will bring. This alters how we evaluate risk and what our expectations are of the future. As a result, asset prices become volatile and market participants become more risk averse by, for example, selling their assets fast and at prices below market value or postponing investments altogether. Simultaneously, when future outcomes are no longer foreseeable, borrowers want to borrow money in order to stay solvent and have enough liquidity to bridge the crisis. Lenders, on the other hand, become reluctant to lend money because they are uncertain about whether they will be paid back in the future, i.e. there is a credit tightening. Subsequently, households and firms are no longer able to consume or invest as they had initially intended. Firms delay their investment plans, cut supply and stop hiring people. Households lose their jobs, decrease consumption and may even default on their debts. Corporate bankruptcies and household payment suspensions ultimately translate into more credit losses for banks. Distressed banks further restrain credit supply in the economy… and we have a chain reaction that amplified the initial shock – a domino effect.

The situation that is described above is what one would call a *systemic event,* or the materialization of *systemic risk.* Systemic risk is a concept that has gained a lot of attention during the last decades, not least after the 2007-2009 great financial crisis. Even though there is no commonly accepted definition of systemic risk, the systemic event itself can be illustrated by a few markers. A systemic crisis is defined as a situation where a country's financial system experiences great distress and where the distress also spills over to the real economy such that economic growth and welfare suffers materially (Hartmann et al. (2009)). The spillover may result in, for example, corporate defaults, extensive falls in asset prices, specifically related to housing and commercial property, or extensive repercussions for households in the form of unemployment or difficulties to repay debts (Kaufman and Scott (2013)). Systemic events often have three things in common. First, they are, initially, individual events. Second, they manage to disrupt the financial system, by breakdowns in all or parts of the system at the same time, and third, they have major negative impact on the real economy. A systemic crisis can be triggered by an exogenous event or come from within the economy or financial system itself through the prior build-up of imbalances, often due to excessive credit growth.

Why is the financial system particularly susceptible to systemic risk? De Bandt and Hartmann (2000) suggest three features of the financial system which makes it more vulnerable to systemic risk than any other sector of the economy. The first feature concerns how banks and the banking system are structured. Banks can have their deposits withdrawn at any time, but only a small fraction of it must be held in liquid reserves. When exceptionally high withdrawals occur, the reserves will not be enough and lead to liquidity problems, even though the bank may be solvent in the long run. The network structure of the financial market is another feature. Not only banks, but many other financial intermediaries, are part of a complex global network with large exposures through the interbank market, wholesale and retail markets, as well as in payment and settlements systems. A failed payment obligation can therefore affect the ability of other institutions to meet their payment obligations, and so on. The third feature, as originally presented in Stiglitz (1993), concerns the information and control intensity of financial contracts, i.e. the intertemporal attribute of financial contracts and their credibility. Future asset values are based on current expectations and contract terms are set depending on whether we expect that future cash flows will be paid out or not. Hence, if there is reason to believe that the credibility of such prospects is questioned, resulting altered market expectations may lead to large movements in asset prices, which could be a starting point for a systemic event. Volatility, together with systemic risk, are essential and important to understand, assess and monitor, due to the inherent vulnerabilities in the financial system and their potential to spill over to the real economy. This is essentially why banks and other financial institutions are subject to heavy regulation and supervision.

Measures of systemic risk and volatility in financial markets

Recent crises have stimulated the development of tools for measuring systemic risk in order to monitor and foresee systemic breakdowns. In addition, specific institutions, such as for example the European Systemic Risk Board (ESRB) in Europe and the Office of Financial Research (OFR) or Financial Stability Oversight Council (FSOB) in the United States, have been formed to assist in this purpose. Broadly speaking, systemic risk measures attempt to quantify the extent of the losses resulting from shocks hitting the system, i.e. to gauge the subsequent increase in tail co-movement resulting from financial distress in the system. For these reasons, the measures must be designed in a way that they capture the systemic nature of risk and shock transmission of firms co-operating in a system or network.

The recent advance of systemic risk measures has been fast and sizable, and the majority of suggestions for measuring systemic risk focus on either measuring the systemic risk of the whole system or that of individual institutions. These approaches aim at detecting *systemically important financial institutions* or help to produce warning signals that can be used to mitigate an impending crisis and its potentially damaging effects. Nevertheless, no unified method, or best practice, has emerged and measurement can take several different approaches. For example, one may focus on firm-specific characteristics obtained from firms' balance sheets (e.g. size, leverage, maturity mismatch, asset quality, cross-holdings of assets etc.). This is typically done by supervisory authorities that have access to comprehensive data. One may also focus solely on market data exploiting the idea that market prices should reflect all information available and therefore can be used to infer the riskiness of an asset, as perceived by the market (e.g. by analyzing stock returns, CDS spreads, option prices etc.). Another measurement approach is looking at correlation, contagion and spillover effects. These have the interconnectedness aspect of systemic risk in focus and are motivated by the argument that if there are firms with large spillover effects, then simultaneous failures are more likely to be observed. Hence, the number of spillover channels, and the extent to which risk actually spills over, can be used as a proxy measure of systemic risk, see for example Lehar (2005), Iori et al. (2006), Cont et al. (2010), Betz et al. (2016) and Billio et al. (2012). Of course, no measure is perfect, and all of the above-mentioned efforts at measuring systemic risk have their flaws. The mere fact that *systemic risk* has no exact definition makes measurement problematic. Suitably, Benoit et al. (2017) describe systemic risk as "*hard-to-define-but-you-know-it-when-you-see-it*". Systemic risk is therefore usually defined from the perspective of what it affects and how, and often ex-ante. Billio et al. (2012) and Di Cesare (2018) provide comprehensive reviews of different measures of systemic risk that are commonly used among both policymakers and academics.

Closely connected to systemic risk is volatility. Erroneously, volatility is sometimes used interchangeably with risk. Risk is however concerned with the *probability* of something happening, for example a loss on an investment, whereas volatility tells us about the *magnitude* of a fluctuation or happening. Consequently, one might view volatility as a type of risk and a specific measure of risk. Predicting the volatility of any financial asset is one of the most fundamental tasks for anyone dealing with investment decisions and risk, especially related to asset pricing and optimal portfolio allocation as many valuation methods for derivatives have volatility as the key input factor. However, volatility, like systemic risk, is not easily observed and must therefore be estimated.

The most basic way to estimate volatility is to calculate the standard deviation, which is simply a statistical approximation of how much something deviates from its typical movement. However, in order to calculate volatility in this way, one has to make some assumptions about the underlying return generating process of the asset. This is not always easy as different kinds of assets will exhibit different properties in their price series. Financial time-series data, such as returns of stock prices, typically exhibit leptokurtosis, which means that the distribution of returns has 'fat tails' (Mandelbrot (1963), Fama (1965)). Essentially this means that the probability of an extreme outcome is always higher than what a normal distribution would predict. This tendency is also stronger for higher frequency data.

Consequently, there are some empirical patterns that are attributable to the volatility of financial time-series (see e.g. Cont (2000) for a complete review). First, volatility tends to be mean-reverting. That means that, over time, volatility tends to go back to its average historical level. Second, volatility is typically clustered and exhibits significant autocorrelation. This means that periods of low volatility are often followed by low volatility, and periods of high volatility are often followed by high volatility. Third, changes in the volatility of an asset tend to be negatively correlated with that asset's return (Black (1976)). This observation is referred to as the 'leverage effect', where a negative shock leads to a higher variance in the next period compared to what a positive shock would have done.

Following these stylized facts there are many ways to estimate and model volatility. Some of the more standard approaches include models from the ARCH(*q*)/GARCH(*p,q*)[3] family (Engle (1982), Bollerslev (1986)), that include an autoregressive part (of order *p*) and/or a moving average component (of order *q*) to model volatility dynamics. Volatility can also be derived from option prices, in which case it is called *implied volatility*. In this setting, using, e.g. the Black-Scholes formula of Black and Scholes (1973), volatility is "implied" from the market price of European options[4]. Other volatility estimation approaches include stochastic volatility models, such as that by Heston (1993), in which we assume that the price of an asset is determined by a stochastic process. Most academics agree on the fact that volatility can be modelled and predicted to a large extent, however methods differ quite broadly. Nevertheless, the modelling and forecasting of volatility is by far one of the most actively researched areas within empirical finance and financial economics and it is the key ingredient to any form of decision-making.

A common misconception is that it is only high volatility that is worrying. In fact, low volatility may be just as worrying. Periods of low volatility are often accompanied by credit growth and higher risk-taking in the economy in general, as economic agents extrapolate the low volatility environment of today into the future, which may lead to a crisis (Minsky (1992)[5], Danielsson et al. (2018)). The term *animal spirits,* established in Keynes (1936), refers to the states of optimism or pessimism held by economic actors and how these states influence decisions made today hence affecting future outcomes. Principally, when market risk changes, risk-taking *behaviour* will also change (Hayek (1960), Minsky (1992)). The materialization of systemic risk is often combined with either unusually high or low periods of volatility, and volatility itself can be a trigger, or tipping point, for crises. Both phenomena are however, related and may act as each other's transmitters. As expressed in Prasad et al. (2005, page 494) "*crises can be regarded as particularly dramatic episodes of volatility"*.

[3] (G)ARCH is an abbreviation of General Auto-Regressive Conditional Heteroskedasticity.

[4] European options are not necessarily from Europe. An option is denoted "European" when it may only be exercised at the expiration date, as opposed to American options, that may be exercised at any time before, but also on, the expiration date.

[5] Minsky describes this as the 'instability hypothesis' where "stability is destabilizing".

Summary and contributions

The thesis collects four independent, although not unrelated, papers, dealing with issues in empirical financial economics with particular focus on systemic risk and volatility in financial markets. Through the use of quantitative methods, all four papers provide new empirical findings to the research topics and contribute with new knowledge to the existing literature.

Systemic risk and centrality – the role of interactions

Asgharian, H., Krygier, D. and Vilhelmsson, A.

In the first paper, we analyze the joint effect of centrality and other characteristics that are important in determining banks' systemic importance. Somewhat surprisingly, the impact of this, conjectured, joint interactive effect of centrality and other characteristics, has not been investigated before, even though the impact of firm characteristics and that of centrality, i.e. the degree of interconnectedness, are extensively studied in isolation (see e.g. Adrian and Brunnermeier (2016), Saunders et al. (2019), Cai et al. (2018)). Therefore, first, we investigate the direct influence of *centrality* on systemic risk. Second, we analyze its moderating effect, which answers if, and how, other bank specific risk factors, such as *Value-at-Risk* or *leverage*, make centrality more, or less, important for a bank's contribution to the systemic risk of the financial system.

We use ΔCoVaR (Adrian and Brunnermeier (2016)) as our preferred measure of systemic risk. ΔCoVaR is a market-based measure that takes return losses on market equity as inputs and is defined as the change in VaR of the financial system conditional on another institution being in financial distress. In simpler words, how much more financially distressed does the financial system become if another institution undergoes financial distress. The motivation of ΔCoVaR as a systemic risk measure lies in the fact that when there is stress in financial markets, the values of assets tend to co-move more. This leads to spillover effects from one institution to another that may amplify the initial shock or stress event. By estimating

ΔCoVaR one may therefore estimate the dependency between an institution's riskiness and its contribution to overall risk in the financial system. The greater the dependency, the more systemically important is the institution.

To create a network and estimate each bank's importance in the network (its centrality or interconnectedness) we use data on loan syndication activities among banks. The data on loan syndication activities provides historical information on the terms and conditions of deals in the global commercial and industrial loan market. It is a substantial data set and has been used in, for example, Ivashina et al. (2015) and Sufi (2007). We construct a network of all US lenders involved in the recorded syndicated loans. Specifically, the network is constructed for a total of 7,740 banks and financial firms. For each quarter t, we construct a matrix with 7,740 rows and columns where the element in row i and column j is equal to the number of common outstanding syndicated loans of banks i and j in that quarter. We next construct six centrality measures, each one being different according to a few assumptions about the length of the syndicate. We also include other variables besides centrality that are important when it comes to determining the riskiness of a financial institution. These are *VaR, size, leverage, non-performing loans* and *non-interest income.* All of these variables have a solid ground in the literature.

To explain ΔCoVaR and to examine the potential moderator effect of centrality, we estimate panel regressions with ΔCoVaR as the dependent variable, and centrality, together with the five risk measures mentioned previously as well as their interaction with the centrality variable, as the explanatory variables. Our main finding is that centrality indeed is an important variable to consider when determining the systemic importance of an institution, but not only by its direct effect. Rather, "being central" impacts the importance of other variables when determining riskiness. This effect is especially large for *VaR*, i.e. *VaR* is more important as an indicator of riskiness for an institution that is also highly interconnected, i.e. central in the network. A bank's contribution to systemic risk, as measured by ΔCoVaR, given *VaR*, is about four times higher for a bank with two standard deviations above average estimated network centrality, compared to a bank with average centrality. The effect is significant both in recessions and normal periods and is more pronounced the more central a bank is. Our results also indicate the opposite. *VaR* of non-central and small banks has no, or very small, implication for systemic risk. Neglecting this indirect moderation effect of centrality severely underestimates the importance of centrality for "risky" banks and overestimates the effect for "safer" banks.

Implicit government guarantees and banks' stock returns

Krygier, D.

Systemically important institutions are often termed *too-big-to-fail* due to their special role in the financial system. Because of this governments, and market participants, often treat these institutions differently. Banks are indeed special because they mobilize and allocate capital and make possible the channelling of funds from those who have more than they need to those who have less than they need. However, banks are also special because their failure will involve extensive repercussions on the whole financial system and generate significant economic costs in the form of large declines in output, growth and investments. Bank frights and financial crises almost always precede economic downturns and concerns about bank distress and financial instability has led governments to develop necessary safety nets during the last century.

When an important bank is close to default, or defaults, the rest of the economy will suffer in some way due to the bank's provision of vital financial services. One bank's failure will also likely affect the solvency of other banks. However, the resulting cost to society that this spillover may incur is not wholly internalized by the bank or financial institution itself, rather it rests at the shoulders of the government and ultimately the tax payers. Banks that are *too-big-to-fail* are hence assumed to be implicitly protected by the government meaning that they (and their creditors) will be saved, *bailed-out,* if the financial institution goes into bankruptcy. The expectation of receiving such protection leads to several problems and distortions. When the cost of risk materialization is not entirely internalized, financial institutions will have incentives to take on excessive risk, and their cost of funding will typically be lower since risk is mispriced. This empirical fact is established in a number of studies including O'Hara and Shaw (1990), Stern and Feldman (2004), Mishkin (2006), Acharya et al. (2013) and Kacperczyk and Schnabl (2011) to name a few.

In the second paper, I therefore examine whether being *too-big-to-fail* translates into lower risk-adjusted returns among banks. The anticipation of government support should ideally be visible in the market in the form of a lower risk premium, since the implicit guarantee from the government is a form of protection that will reduce the overall risk of the *too-big-to-fail* institution. This hypothesis is established and confirmed in e.g. Gandhi and Lustig (2015). The *too-big-to-fail* doctrine closely links *size* to systemic importance, however this need not always be the case, as we have seen in e.g. Asgharian, Krygier and Vilhelmsson (2020) and as is concluded in i.a. Zhou (2009), Laeven et al. (2014) and by public institutions such as the Office of Financial Research (OFR (2017)). Some financial institutions, that are relatively small in comparison to others, are still treated as *too-big-to-fail* because of their essential role in the financial system. Also, *size*, traditionally measured by the book or market value of assets, has not always been a unique criterion for bail-out policies. This justifies measuring systemic importance not solely with *size,* as done in Gandhi and Lustig (2015), but with actual systemic risk measures that ought to be broader and that consider not only *size* but also other important attributes that determine systemic importance. The methodological approach of this paper is hence from Gandhi and Lustig (2015) who find that large commercial banks stocks have significantly lower risk-adjusted returns than small and medium-sized bank stocks, in spite of the fact that large banks are more levered, i.e. risky. The authors argue that this *size premium* in large financial institutions is a compensation for financial crisis risk, i.e. compensation for being *too-big-to-fail*, and an absorption, by the government, of the systemic banks' tail risk.

I use Δ*CoVaR* and the *marginal expected shortfall* (MES) to measure systemic importance and to distinguish systemically important institutions – the institutions most likely to be classed as *too-big-to-fail* by supervisors and to receive protection in crises. The link between systemic importance and equity returns is then analyzed by sorting institutions into portfolios based on their level of ΔCoVaR and MES at a certain time and over time. Implicit guarantees are not measured directly in this paper, rather they are proxied for by examining whether there are any differences in risk-adjusted returns between highly systemic and less systemic banks, while controlling for common risk factors. Within this asset pricing framework, my results do not point towards the perception that implicit government guarantees infer lower risk-adjusted returns. With high coefficients of determination and alphas close to zero, systemic importance seems to be accounted for by the included standard risk factors: the three factors of Fama and French (1992) and two additional bond risk factors. Alternatively, *too-big-to-fail* is not identified, or identified in a different way, by market participants.

Equity volatility and leverage - loan level evidence

Krygier, D. and Vilhelmsson, A.

Since the seminal paper of Engle (1982), the time series behaviour of equity volatility has been studied extensively. However, we still know surprisingly little about the determinants of firm specific (idiosyncratic) equity volatility and it also differs a lot across firms. Even if a large part of idiosyncratic volatility can be diversified away, the total volatility – *systematic* and *idiosyncratic* – matters. Volatility matters for all investors who are imperfectly diversified (Campbell et al. (2001)), it matters for trading frictions (Shleifer and Vishny (1997)) and it is a key input to derivatives pricing. Understanding the firm level determinants of equity volatility is not only important for the reasons just stated, but it also constitutes a first step in understanding the variation in aggregate stock market volatility over time as discussed in e.g. Campbell et al. (2001), Brandt et al. (2010) and Bekaert (2019).

The third paper contributes to the understanding of firm level determinants of volatility by studying the relationship between firm indebtedness (leverage) and equity volatility using a large dataset on detailed loan level information. The data allows us to identify on exactly what day a firm is given a new loan as well as the size of the loan. Therefore, we can calculate the change in volatility for a given firm shortly before and after it has experienced a large increase in leverage. The identification strategy hence entails a large within-firm change during a short period of time.

Measuring the relationship between volatility and leverage is nevertheless challenging for several reasons. First, firms choose their leverage strategically, and firms that are safe in a business sense (have low asset volatility) will generally have high financial leverage, which makes it almost impossible to correctly measure the relationship between leverage and volatility in the cross-section of firms. An alternative would be to study changes in leverage over time for a given firm, however this set-up often results in low statistical power since, typically, a given firm's leverage does not change much over time compared to the cross-sectional variation. A further difficulty is that changes in leverage are usually observed from accounting data, and therefore only measured at a quarterly or annual frequency, which makes it difficult to know how and when leverage changes. Still, taking a loan is of course not an exogenous event; the reason the firm takes a loan and the information event around the loan may also affect volatility directly and not only through its effect on leverage. Finally, the level of volatility and the probability of taking a loan may be dependent of each other.

Our approach solves the above problems and our results are highly significant and robust to different specifications. We find that taking a bank loan indeed leads to a large and significant increase in variance. One part of this increase seems to be transitory and one part is permanent, or at least very long-lived. To remedy the mean-reverting attribute of variance we do a difference-in-difference style regression where we calculate the change in the variance of a firm before and after the loan, minus the change in market variance before and after the loan. This decreases the estimated effect of variance to leverage, but the results remain highly significant. A new loan of average size for a firm with average leverage, will, according to our results, increase the firm's equity standard deviation by 4.6 %. We also confirm that the positive and significant relationship between leverage and volatility exists for all firms and is not only driven by high leverage companies. Our results remain robust to different types of loans, as well as to the purpose of the loan.

What drives Bitcoin volatility?

Byström, H. and Krygier, D.

The fourth paper considers volatility dynamics in the Bitcoin market. One of the most intriguing financial innovations of the last decade is, without a doubt, the concept of cryptocurrencies. Bitcoin, being such a cryptocurrency, is the world's largest by market capitalization and it has grown rapidly during the last decade. Bitcoin is also extremely volatile, and predicting the volatility of any currency or asset is one of the most fundamental tasks for anyone dealing with investment decisions and risk management. In addition to the general interest in explaining drivers of price movements in a novel financial market such as the Bitcoin market, there are several other practical reasons for analyzing causes and features of Bitcoin volatility. One example is the introduction of Bitcoin futures, trading in two of the worlds' major derivatives exchanges, the Chicago Mercantile Exchange and the Chicago Board Options Exchange. In order to compute margins required by clearing houses and brokers standing behind the buyers and sellers in derivatives markets, one needs to be able to do predictions of the Bitcoin volatility. Furthermore, the launch of Bitcoin futures has also spurred market participants trying to get approval for Bitcoin-tracking exchange traded funds. Such developments, leading to a wider range of potential Bitcoin investors, creates a growing need for a deeper understanding of risk and volatility in the Bitcoin market.

In this paper, we look at Bitcoin prices and how the volatility of Bitcoin returns is linked to corresponding volatilities in the gold market, currency market and stock market. We also consider the link to the general level of risk and uncertainty in the economy measured by the economic policy uncertainty index (Bloom, Baker and Davis (2016)) and a systemic risk indicator for the US banking system (Saldías (2013)). Finally, we link Bitcoin volatility to Google internet search volumes on phrases like '*bitcoin*', '*gold price*', '*war*' and '*cyber-attack*' in order to account for the potential importance of retail investors. By looking at Google search volumes, we believe that we can isolate and control for, at least to some degree, the share of the driving forces behind Bitcoin volatility that are related to the retail market. We look at volatilities at different sampling frequencies, with daily, weekly and monthly windows for volatility calculations using daily data. The main question that we are trying to answer is what drives Bitcoin volatility and, in a later stage, do these drivers have any forecasting ability. Our main finding, based on correlations, Granger correlations, ordinary least squares regressions and vector autoregressions, is a fairly strong positive link between Bitcoin volatility changes and search pressure changes on Bitcoin-related words on Google, particularly, and as expected, for the search term '*bitcoin*'. We further show, using several different loss functions, that Google search activity can be used to make improved predictions of Bitcoin volatility. Overall, internet activity seems to be relevant for the behaviour of the Bitcoin market. For anyone who wants to explain, understand or predict volatility it could be worth acknowledging search pressure on search engines like Google. Additionally, the significant link between Google search volumes and Bitcoin volatility points at retail investors, rather than large institutions investor, being major drivers of volatility dynamics.

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Table of Contents

Systemic risk and centrality - the role of interactions

Asgharian, H., Krygier, D. and Vilhelmsson, A.

Abstract

In this paper, we analyze to what extent the contribution of banks to systemic risk depends on their centrality in financial networks, and if the contribution to systemic risk of standard bank-level risk measures in turn depends on banks' centrality. Our main finding is that centrality is an important determinant of systemic risk, for all but the smallest banks, but not only by its direct effect. Rather, its main influence is to make other firm-specific risk measures, such as Value-at-Risk, more important for highly connected banks. Neglecting this indirect moderation effect of centrality severely underestimates the importance of centrality for "risky" banks and overestimates the effect for "safer" banks. Our results are robust to different specifications of centrality. We also show that, even though size and centrality are related, the inclusion of centrality provides additional and valuable information when assessing the systemic importance of banks.

Key words: systemic risk, network, centrality, loan syndication, CoVaR
JEL codes: G21, G18

1 Introduction

Systemic risk is the risk of a crisis in the financial sector with consequential negative spillover effects to the real economy. To understand and manage systemic risk, it is important to understand both macro and micro determinants of systemic risk. Macro determinants focus on the overall structure of the financial system, whereas the micro approach focuses on the marginal contributions of individual actors to systemic risk. Our paper is primarily focused on the micro level, but it includes the macro level by studying the banking network. Our basic idea is simple. We suggest that a bank's centrality should not be considered a separate cause of systemic risk. Rather, we suggest that centrality affects how much a bank's "riskiness" contributes to systemic risk. Statistically this means we should treat centrality as a moderator variable. We, therefore, investigate how the contribution to systemic risk of standard bank-level risk measures varies depending on the bank's centrality. We show that risky banks contribute extensively to systemic risk only if they are also centrally placed in the financial network.

Somewhat surprisingly, the impact on systemic risk from the interaction effect of centrality and bank characteristics has not been investigated before, though both the impact of firm[6] characteristics (Adrian and Brunnermeier (2016), Saunders et al. (2019), Brunnermeier et al. (2019)) and that of network centrality (Cai et al. (2018), Martinez-Jaramillo et al. (2014)) are studied in isolation. The treatment of centrality and other bank risk indicators as separate and independent sources of systemic risk is also reflected in current systemic risk regulation (BCBS) (2018)).

To calculate systemic risk, we use Adrian and Brunnermeier's (2016) *ΔCoVaR,* and we obtain centrality by using the network of banks participating in the loan-syndication market. The paper most closely related to ours is that of Cai et al. (2018), who also calculate an interconnectedness measure from syndicated loans data and use it to explain different measures of systemic risk, including *ΔCoVaR*. Our paper differs from Cai et al. (2018) in several aspects: they measure interconnectedness by commonality of asset holdings, whereas our paper considers actual network connections between banks. Hence, our paper complements Cai et al. (2018) by focusing on the centrality of a bank rather than

[6] The word 'firm' is used interchangeably with the word 'bank', if not otherwise specified.

balance-sheet overlap. Further and most importantly, Cai et al. (2018) do not interact firm characteristics with their commonality measure, but treat it instead as a separate source of risk.

The data on loan syndication is obtained from the Thomson Reuters DealScan database, which provides historical information on the terms and conditions of deals in the global commercial and industrial loan market. It has been used by, for example, Ivashina et al. (2015) and Sufi (2007). We consider two banks to be linked when they participate in the same loan syndicate and we further calculate six different centrality measures based on the loan syndication data matrix.

Using panel data regressions to explain *ΔCoVaR*, our estimate of systemic risk, our main finding is that centrality is an important determinant of systemic risk contribution, for all but the smallest banks. However, not by its direct effect. Rather, its main influence is to make *Value-at-Risk (VaR)* much more important for highly connected firms. A bank's contribution to systemic risk from *VaR* is about four times higher for a bank with two standard deviations above average network centrality, compared to a bank with average network centrality. Current systemic risk regulation takes centrality into account as one of five categories used for calculating systemic importance, but it does so as a standalone component. By giving each of the five categories that contribute to systemic risk equal weight, current regulation cannot capture that the importance of firm characteristics varies with centrality, hence underestimating the importance of centrality for risky banks (including Citigroup, Bank of America, and Morgan Stanley) and overestimating the effect for "safer" banks. Our results are robust to different specifications of centrality and still remain so after simultaneously allowing also size to act as a moderator variable. This suggest that despite the fact that size and centrality, in isolation, are important variables to consider for systemic importance they do not measure the same thing. Size has typically been used as a criterion for identifying systemic importance, as a larger balance sheet increases the probability of larger spillover effects and contagion (see e.g. Acharya et al. (2010, Brownlees and Engle (2016)). However, spillover effects and contagion predictably depend on how interconnected the financial system is and more specifically how interconnected, or central, individual institutions are in that system. Therefore, even though size and centrality are related, the inclusion of centrality when assessing determinants of systemic risk for banks provides additional and valuable information. This paper is the first that empirically confirms this outcome.

The structure of the paper is as follows. Section 2 introduces the concept of systemic risk in terms of its meaning, measurement, regulation, and related literature. Section 3 presents the data and discusses the variable choices made in our models. In Section 4, we introduce the methodology of $\Delta CoVaR$, network theory, and network centrality in the loan syndication market. Section 5 presents and discusses our main results and contributions, and Section 6 concludes.

2 Systemic risk

Systemic risk can be defined as the risk of a crisis in the financial sector with resulting negative spillover effects to the real economy. The important features are that all or parts of the system are affected at the same time by a disruptive event, and that it has damaging effects to the real economy, in terms of negative externalities (Kauffman and Scott (2003), Acharya et al. (2012)). For a comprehensive and fairly recent review of the topic, see Benoit et al. (2017).

2.1 Regulation

Since 2012, the Basel Committee on Banking Supervision (henceforth BCBS) has ranked the world's largest financial institutions[7] according to their systemic importance. The current method described in BCBS (2018) uses five categories: *size, interconnectedness, substitutes* or *financial institution infrastructure, cross-jurisdictional activity*, and *complexity*. These five categories are computed from underlying indicators and the total "systemic importance score" is calculated as an equally weighted average from the five categories. Details of calculations as well as potential problems with the current methodology, are discussed in Benoit et al. (2019) and in the original BCBS (2018) methodology assessment paper. The 29 banks with the highest systemic risk score are, among other things, subject to additional capital requirements calculated based on which of five "buckets" they end up in. The additional charges range from 1% additional equity-to-risk-

[7] Total exposure >200 billion euro, with exposure measured as in the leverage ratio framework of BIS (2014).

weighted capital up to 3.5% in the highest bucket. The "bucket list" for 2019 is available in FSB (2019)[8].

2.2 Related literature

Three interrelated fields of research have emerged within the area of systemic risk. The first concerns the *measurement* of systemic risk. Systemic risk measures attempt to quantify the extent of the loss resulting from shocks hitting the system and to gauge the potential increase in tail co-movement stemming from financial distress in the system. Therefore, these measures must be designed such that they capture the systemic nature of risk and shock transmission of firms cooperating in a system or network, the cross-sectional component. Several measures try to take this into account, one of which is the Adrian and Brunnermeier (2016) *ΔCoVaR,* a market-based measure of systemic risk designed to capture the cross-sectional tail dependency between a firm and the whole financial system. It is directional and asks the question of how much does system-wide risk increase should an individual firm be in financial distress? The conditioning event can also be reversed to answer such questions as which actors are most at risk should a crisis occur? *ΔCoVaR* is described in more detail under the methodology section of this paper. Other empirical measures based on publicly available data are, for example, Brownlees and Engle's (2016) SRISK and the distressed insurance premium (DIP) by Huang et al. (2012). Additional systemic risk measures include Brownlees and Engle's (2012) marginal expected shortfall (MES), systemic expected shortfall (SES) of Acharya et al. (2012), and Banulescu and Dumitrescu's (2015) component expected shortfall (CES). The main difference between the mentioned measures is the conditioning event, i.e. how "distress" or a "tail event" is defined.

A natural next step after measuring systemic risk is to relate the risk estimate to possible firm-level *determinants* of the degree of systemic importance among financial institutions, and subsequently study the *predictive ability* of these determinants to mitigate, or even prevent, a future systemic crisis. This field is the most well tilled, most likely due to the need to incorporate systemic risk into financial regulation after the financial crisis, but also because market-based

[8] FSB 2019 list of globally systemically important banks (G-SIBs).

econometric methods, like *ΔCoVaR*, are silent about what causes a firm to contribute to systemic risk. The aim of this part of the literature is thus to predict a firm's future systemic risk contribution. The three firm-specific characteristics that have been found to best explain systemic importance of individual financial institutions are size (Pais and Stork (2011), Black et al. (2016)), leverage (Brunnermeier at al. (2019), Kaufman and Scott (2003)), and *VaR* (Adrian and Brunnermeier (2016)). Additional characteristics, such as the degree of noninterest income (*NII*) and nonperforming loans (*NPL*) have also been shown to predict systemic risk contribution (see for example De Jonghe et al. (2015) and Brunnermeier et al. (2019)).

The third field deals with *interconnectedness* or the network perspective of systemic risk. Risk spillover among financial institutions and firms results both from direct linkages between them, in terms of, for example, interbank transactions when it comes to banks (Allen and Gale (2000)), but also the commonality of asset holdings, which refers to the holding assets with similar risk exposure (Cai et al. (2018)). Network theory is the main estimation tool to quantify spillover effects. This area is less explored and was initiated by Allen and Gale's (2000) study of how the banking system responds to contagion under different system network structures and further explored in Billio et al. (2012). The network analysis literature deals primarily with networks and their structure and is concerned with the joint loss distribution of all market participants, see for example Hautsch et al. (2014). Cont et al. (2012) study the mechanism of shock propagation when bank size and the degree of interconnectedness is taken into account. They find that institutions tend to be more systemically important if they have large interbank exposures, and also that an institution's position in a particular network plays an important role when it comes to its systemic significance. To briefly summarize the section on interconnectedness, one could say that in addition to the traditional "*too-big-to-fail*" view, a "*too-central-to-fail*" equivalent is included in the ongoing debate on systemic risk.

Our paper is closely related to Cai et al. (2018), who also study the interconnectedness of banks and systemic risk. Additionally, they use the same DealScan database as the source of their loan syndication data. However, our paper complements Cai et al. (2018) by focusing on the risk spillover source that results from direct linkages between banks, whereas they consider commonality of asset holdings. Based on an interconnectedness measure that considers the "distance" (similarity) between two banks' syndicated-loan portfolios, they find that banks with similar asset holdings contribute more to systemic risk and that this effect is exacerbated during recessions. They also find that interconnectedness is positively related to size and diversification level, as well as to other systemic risk measures such as *ΔCoVaR*, *SRISK* and *DIP*.

Acemoglu et al. (2015) study systemic risk and stability in financial networks and argue that as long as negative shocks are sufficiently small, a network with a more diversified pattern of interbank liabilities (i.e. a densely connected system) boosts financial stability. Fragility in the financial system however increases if the magnitude of shocks increases beyond a certain threshold. The main takeaway from their paper is the finding that the same factors that are beneficial from the systemic risk perspective under certain conditions, increase systemic risk under other conditions. The relationship between network structure and the extent of financial contagion is, however, debated. For example, Allen and Gale (2000) suggest that in a more dense (i.e. more connected) financial network, losses are divided among more creditors, which in turn reduces the impact of distress of an individual institution towards the system. Interconnection hence enhances financial stability. On the other hand, the more traditional view is that a more interconnected system increases the likelihood of a systemic collapse. This view is shared by, for example, Gai et al. (2011), Ladley (2013) and Vivier-Lirimont (2006).

Our paper is related to all three research fields, but it contributes most to the second and third by being the first study to investigate if firm-specific variables such as *VaR*, *size*, extent of non-performing loans[9] (henceforth *NPL)* and non-interest income[10] (henceforth *NII)* vary in importance depending on the centrality of the firms. Not only do we investigate whether centrality contributes to systemic risk directly, but also its moderating effect, which answers if one unit of e.g. *VaR,*

[9] Non-performing loans, also called "bad debt", are defined as bank loans where the borrower has not paid any interest or instalments for (usually) 90 days or more.

[10] Non-interest income is defined as income generated by operations that are outside of the bank's core intermediation operations. An example of a core operation for a bank is lending money and taking deposits. Examples of non-interest income generating activities are different types of fees, trading revenue or investment banking activities.

size or any other risk characteristic, contributes more to systemic risk for a firm that is central than it does for a non-central firm.

3 Data

The paper combines data from several sources. Data on macroeconomic variables[11] is from FRED (Federal Reserve Bank of St. Louis Economic Data) and stock return data from CRSP are used to compute *ΔCoVaR*. Our centrality measure is based on loan-level information from DealScan, and necessary firm-specific information is taken from Standard and Poor's Compustat/CapitalIQ. We define our initial sample as the 1,823 financial institutions[12] in Adrian and Brunnermeier (2016) and we can match 738 of these companies to the DealScan set using the matching key from Chava and Roberts (2008) and Forssbaeck et al. (2018). Out of these companies, 264 provide the information about the syndicate structure of the loan which we need in order to calculate the centrality measure. As a point of reference, Cai et al. (2018) have data for 38 companies only.

3.1 Data for *ΔCoVaR*

We obtain daily stock return data from CRSP for the time period 1995 to 2016. Adrian and Brunnermeier's (2016) state variables[13] are used to capture tail-risk dependence over time and make *ΔCoVaR* time varying. Seven state variables are obtained from FRED:

i. The change in the 3-month treasury bill yield.
ii. The change in the slope of the yield curve. This is the yield spread between the 10-year and 3-month treasury bills.
iii. The TED spread (3-month LIBOR minus the 3-month secondary-market treasury bill rate).

[11] By macroeconomic data we mean data on real economic variables, such as for example different interest rates.

[12] Adrian and Brunnermeier (2016) are using PERMNOS, a security rather than a company identifier, so companies with dual class shares are included twice in their sample. We exclude duplicates.

[13] State variables refer to variables that may tell us something about the 'state' the economy is in, in other words the macro data. More details about the state variables used can be found in Adrian and Brunnermeier (2016).

iv. Change in the credit spread between Moody's Baa-rated bonds and the 10-year treasury rate.
v. Weekly market CRSP value-weighted return.
vi. Weekly real estate sector return (SIC 65–66) in excess of the financial sector return (K. French data).
vii. Equity volatility (22-day rolling SD of daily CRSP equity-market return).

Variables ii. and iv. are assumed to capture time variation in return tails. Variables v. and vi. are used as controls for equity market returns. Finally, i., iii., and vii. are factors or indicators to capture future economic activity and inflation (i.), short-term liquidity risk (iii.), and uncertainty and investor sentiment (vii.).

3.2 Data for centrality measures

To calculate a centrality measure for each lender, we need data on something that represents "bank-to-bank activities". We use data on syndicated loans provided by the Thomson Reuters DealScan database to measure interbank activities. Specifically, we measure how central a bank is in the syndicated loan market. We believe this is a good proxy for interbank connections because it is more likely that a bank with many connections on the loan syndication market also has many connections (with the same counterparties) on the interbank market. Another reason for using the loan syndication market is its size. For example, in the US, the loan-syndication market alone exceeds the public debt and equity markets together (Cai et al. (2018)). By examining loan syndication activities, we are also able to study patterns of balance-sheet overlap in banks' loan portfolios. Cai et al. (2018) show that banks tend to choose the same syndicate partners over time. This is consistent with the idea that banks within the same syndicate group also engage in other business transactions, apart from syndication.

DealScan provides information on the terms and conditions of deals in the global commercial loan market, including the loan syndication market and has been used in, for example, Ivashina et al. (2015) and Sufi (2007). The database contains more than 300,000 loans over the period 1985 to 2016, and most of the loans are syndicated. A syndicated loan is a type of loan offered by a number of banks or financial institutions. It is normally coordinated by one bank, called the lead arranger, and the other banks typically participate more passively in the syndicate.

3.3 Data for accounting variables

Based on the literature review, a set of accounting variables are chosen as the determinants to explain and predict systemic risk contribution. These variables consist of *VaR*, *leverage*, *size*, the ratio of *non-performing loans* to total assets, *non interest income* to interest income, and, lastly, our *centrality measure* (described in detail in Section 4.2). We briefly describe each variable and its economic importance. Exact item identifiers for the variables in CapitalIQ can be found in the appendix.

i. *Value-at-Risk*: *VaR* is a widely used risk measure in both theory and practice, and as a regulatory tool. It calculates the maximum potential loss that we may expect for a firm with some probability q, over a holding period of n days. Calculation details are given in Section 4.1.

ii. *Size*: Size is considered one of the standard firm-specific systemic risk determinants in the systemic risk literature. We measure size by the log of market capitalization. Large banks are different from small banks not only in asset values, but larger banks also tend to engage more in non-lending activities, generate more non-interest income, hold less risk-weighted capital, have higher leverage, have less deposit funding and are more organizationally complex. Naturally we therefore expect a large bank to contribute more to systemic risk compared to a smaller bank.

iii. *Leverage*: We define leverage as total assets divided by the book value of equity. Leverage tells us something about the solvency of a firm and is one of the standard firm-specific systemic risk determinants in the literature. Leverage is expected to increase a firm's contribution to systemic risk. A high leverage ratio increases the likelihood of a firm going into insolvency because a higher share of assets is financed by debt. Hence, if the firm finances its business by a larger share of debt, the higher is the probably that the assets cannot be liquidated upon default and losses given default are expected to be higher.

iv. *Non-performing loans*: An *NPL* is a loan in default or a loan close to default. A loan is classified as non-performing if the borrower has not managed to make agreed upon interest payments or instalments by 90 days or more. The ratio *NPL to total assets* as a firm-specific risk factor is important to consider because high levels of *NPL*s may hold down credit growth and economic activity by deterring banks from undertaking one of their core tasks, providing credit. That is, the variable tells us something about the bank's loan-portfolio quality and accounts for realized credit risk by quantifying credit losses. The relationship between the contribution to systemic risk and the *NPL* rate is therefore expected to be positive.

v. *Non-interest income*: *NII* to interest income as a ratio takes into account how non-traditional a bank is, in the sense that the bank is engaged in non-interest generating activities such as investment banking, venture capital, securitization, and derivatives trading. These activities are often deemed more risky than traditional lending and hence one would expect a positive relationship between *NII* and systemic risk. However, the variable also captures, to some extent, firms' diversification strategies, so the variable's expected sign for its relationship with systemic risk is deemed ambiguous in some cases.

4 Method

In this section, we first describe the method we use to estimate $\Delta CoVaR$ (Section 4.1). We then describe our centrality measures in detail (Section 4.2). Finally, we present the regression model to find the factors that can explain $\Delta CoVaR$ (Section 4.3).

4.1 $CoVaR$ and $\Delta CoVaR$

CoVaR is defined as the *VaR* of an institution, conditional on another institution being in financial distress. It can also be defined in terms of the financial system in which case *CoVaR* measures what happens to the finanacial system's *VaR* when a specific institution is in financial distress, which in turn is measured as that institution having a realized return less than or equal to its own *VaR*. *ΔCoVaR,* therefore, measures by how much the system *VaR* changes if a particular institution goes into financial distress.

We begin by recalling the definition of a firm *i*'s *VaR,* the maximum potential loss (X^i) we can expect for firm *i* with some probability *q* over a holding period of *n* days. In other words, we are looking for the *q*-quantile in the loss distribution. Common choices of *q* are 0.01 (1%) and (0.05) 5%, and we focus on 1% as in Brunnermeier et al. (2019).

$$\Pr\left(X^i \le VaR_q^i\right) = q \tag{1}$$

We can now define the *CoVaR* of the whole finance system *s* conditional on some event $\mathbb{C}(X^i)$ of firm *i* (firm *i* being in financial distress):

$$\Pr\left(X^s \le CoVaR_q^{s|\mathbb{C}(X^i)} \middle| \mathbb{C}(X^i)\right) = q \tag{2}$$

Thus, $CoVaR_q^{s|\mathbb{C}(X^i)}$ is defined by the q^{th} quantile of the conditional probability distribution above. The event $\mathbb{C}\left(X^i\right)$ causing firm *i* to be in financial distress is defined as that firm having reached its *q*%-*VaR* level (i.e., $X^i = VaR_q^i$). We define *s* to be the financial system. Firm *i*'s contribution to systemic risk in the system, termed *ΔCoVaR*, is calculated as

$$\Delta CoVaR_q^{s|C(X^i)} = CoVaR_q^{s|X^i = VaR_q^i} - CoVaR_q^{s|X^i = VaR_{q=0.5}^i} \tag{3}$$

The above classification allows us to calculate the contribution of firm *i* to the systemic risk of the financial system *s*. *ΔCoVaR* simply represents the difference between the *VaR* of the financial system conditional on if firm *i* is in distress or not. Not being in distress is defined as firm *i* operating in "normal times," at its 50%-*VaR* level.

CoVaR is estimated using quantile regressions on weekly equity returns following Adrian and Brunnermeier (2016). A quantile regression of firm *i*'s returns (X^i) on a constant α gives the firm's *q*%-*VaR*, which is simply the estimate of the q^{th} quantile of X^i

$$X_q^i = \alpha_q^i + \varepsilon_q^i \tag{4}$$

$$VaR_q^i = \hat{\alpha}_q^i$$

Similarly, by running a quantile regression of system *j* returns (X^j) on firm *i*'s returns (X^i) plus a constant α, we find the *CoVaR* of the system *s*, given that firm i is at its *q*%-*VaR* level:

$$X_q^s = \alpha_q^i + \beta_q^i X^i + \varepsilon_q^i \tag{5}$$

$$CoVaR_q^{s|X^i=VaR_q^i} = VaR_q^s | VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i$$

Again, *CoVaR* is hence the fitted value of X_q^s given that $X^i = VaR_q^i$ for a prespecified quantile *q*. Firm *i*'s contribution to systemic risk is then given by the following

$$\begin{aligned} \Delta CoVaR_q^{s|X^i=VaR_q^i} &= \left(\hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i\right) - \left(\hat{\alpha}_{0.5}^i + \hat{\beta}_{0.5}^i VaR_{0.5}^i\right) \\ &= \hat{\beta}_q^i\left(VaR_q^i - VaR_{0.5}^i\right) \end{aligned} \tag{6}$$

Note that $VaR_{0.5}^i$ is the median of the return distribution and denotes the "normal" state of the institution. The last equality in equation (6) is proved in Appendix B of Benoit et al. (2013). Assuming the median return of institution i is close to zero, we get

$$\Delta CoVaR_q^{s|X^i=VaR_q^i} \approx \hat{\beta}_q^i VaR_q^i \tag{7}$$

with $\hat{\beta}_q^i$ being the quantile regression coefficient of the market return on the bank return. Since $\hat{\beta}_q^i$ is firm specific, there is no strong cross-sectional dependence between the *VaR* and *ΔCoVaR* (shown in Adrian and Brunnermeier (2016) Figure 1). However, for a given firm, *ΔCoVaR* is proportional to *VaR* with the proportionality coefficient $\hat{\beta}_q^i$ being firm specific. Figure 6 in Benoit et al. (2013) shows the near perfect correlation between *VaR* and *ΔCoVaR* over time for Bank of America.[14]

The above estimations only construct constant estimates. That is, we only observe the average contribution of systemic risk over the chosen time period and nothing about how the contribution changes over time. To construct a time-varying series of *VaR*s, *CoVaR*s and *ΔCoVaR*s that captures the time variation in the distribution

[14] The correlation will still be one when time variation is induced by state variables as in Brunnermeier et al. (2019), Adrian and Brunnermeier (2016) and in this paper. If a DCC-GARCH model is used instead, the correlation will be close to, but not exactly, one (Benoit et al. (2013)).

of X^i and X^j, we need to estimate the conditional return distribution as a function of state variables. That is, we need to assume that equity returns depend on a set of macro variables that are acknowledged to capture the tail risk dependence and expected returns over time. These macro variables were presented in the data section. The estimation is executed following Adrian and Brunnermeier (2016).

4.2 Centrality measures

We use network theory to identify and quantify centrality. The aim of network analysis is to describe the structure of networks by focusing on the relationships between all or a set of actors in the network. The main goal is to identify influential, or central, actors. Networks are important to analyze in the systemic risk setting because they can facilitate and amplify the transmission of shocks, initially often minor shocks, which partly depend on how the network is structured.

A network is made up of points, denoted nodes, with lines that connect them, called edges. We represent the network by an $n \times n$ network matrix $\mathbf{M}$ where n represents the number of nodes in the network. The network matrix is symmetric since if i is connected to j, then clearly j is connected to i. We use two alternative approaches to determine if two firms are connected at time t: the first approach uses the entire duration of the facility (the syndicated loan) joining the two lenders, and the second approach only considers the facility's start date.

Several measures of centrality are based on network theory (for a detailed description, see, for example, Newman (2008). We adapt the eigenvector centrality measure that gives a score (ranking) for each node (actor) that depends on both the number and quality of the node's connections.[15] The aim is to compute an actor's centrality as a function of the number of neighbours it has, its connections in the network, and the importance of its neighbours in the network.

We construct a network of all US lenders involved in the recorded facilities. The network is constructed for a total of 7,740 banks and financial firms, and includes

[15] Mathematical details of eigenvector centrality can be found in for example Bonacich (2007), Bonacich and Lloyd (2001), and Newman (2008).

our initial sample of banks as well as all of the US lenders that participated at least once in the same syndicated loans as the banks in our final sample. More specifically, for each quarter *t,* we construct a matrix with 7,740 rows and columns in which the element in row *i* and column *j* is equal to the number of the common outstanding syndicated loans of banks i and j in that quarter. The eigenvector associated with the largest eigenvalue of the network matrix in each quarter is used as the measure of centrality of banks in that quarter. We construct such a centrality score for all 7,740 banks and then use the scores related to banks included in our sample as an independent variable in our regression analysis. In total, we construct six centrality measures (CM):

- *CM1*: $M_{ij,t}$ is equal to the number of facilities that i and j share in period *t*, for all *t* from the start date to the end date of each facility. *CM1* for lender i at quarter t is equal to element i of the eigenvector associated with the largest eigenvalue of the network matrix **M** in each quarter.

- *CM2*: The network matrix is defined as in *CM1*, but we assume that the link between two lenders decreases exponentially over time after the starting date of the facility contract. More specifically, we specify the total number of connections bank *i* has with all other banks, each quarter until maturity, but allow connections to get weaker over time. We use an exponentially decreasing function to avoid negative values for a link as follows

$$M_{ij,t} = \sum_{f \in F_{ij,t}} \exp\left(-gQ_{f,t}\right), \tag{8}$$

where g is the smoothing parameter (selected as 0.1 for a smooth decrease) and $Q_{f,t}$ is the number of quarters at time *t* since the starting date of facility *f* in which *i* and *j* jointly participate, such that $0 \leq Q_{ft} \leq$ duration of facility *f.*

We sum over all of the facilities that *i* and *j* share in period *t*, which is denoted by $F_{ij,t}$. *CM2* for lender i at quarter t is equal to element i of the eigenvector associated with the largest eigenvalue of the network matrix **M** in each quarter.

- *CM3*: The network matrix is defined as in *CM1*, but we only consider the facility start date to define the link between two lenders in the network matrix. For example, if banks *i* and *j* initiate the syndicate in 2015Q1, this connection is not included in 2015Q2, even though the syndicate might still be ongoing. A connection is visible only in the quarter it is initiated in. *CM3* for lender i at quarter t is equal to element i of the eigenvector associated with the largest eigenvalue of the network matrix **M** in each quarter.

- *CM4*: This measure is based on the *adjacency matrix,* where the element in row i and column j is set to 1 if banks i and j share at least one outstanding syndicated loan in that quarter. More formally the adjacency matrix, $M_{ij,t}$, is defined as

$$M_{ij,t} = \begin{cases} 1 & \text{If } i \text{ and } j \text{ are jointly part of any syndicate in period } t, \\ & \text{facility start date} \leq t \leq \text{ facility end date} \\ 0 & \text{Otherwise} \end{cases}$$

This measure does not take into account the number of connections that the two banks have in each period t. CM4 for lender i at quarter t is equal to element i of the eigenvector associated with the largest eigenvalue of the adjacency matrix **M** in each quarter.

- *CM5*: This measure uses an adjacency matrix, as in *CM4*, but we only consider the facility start date to define the link between two lenders in the network matrix. *CM5* for lender i at quarter t is equal to the element i of the eigenvector associated with the largest eigenvalue of the adjacency matrix **M** in each quarter.

- *CM6*: In the five centrality measures above, we use the network or adjacency matrix, to define the relative centrality or importance of each lender participating in a facility. In *CM6*, we consider being a *lead arranger* of loans as the measure of centrality and importance of a lender in the network. Lead arrangers collect a group of lenders to jointly finance a syndicated loan. They negotiate the price and non-price loan terms and usually retain the largest part of the loan. *CM6* for lender i at quarter t is equal to the number of facilities in which that lender acts as lead arranger of the facility.[16]

[16]We classify a lender as a lead arranger if its role in DealScan is defined as an administrative agent, agent, arranger, book-runner, coordinating arranger, lead arranger, lead bank, lead manager, or mandated arranger. We exclude the cases with no lead arranger or with multiple lead arrangers. This information is then cross-checked with the field "LeadArrangerCredit" in DealScan. For a lead arranger this field should be "Yes."

Note that all of the measures above are calculated based on all 7,740 lenders and all the facilities these lenders have been involved in. We then extract the measures for our sample of 264 firms. Table 1 summarizes the five measures, CM1 to CM5, that are based on the network matrix **M**.

Duration \ **Network matrix**	*Matrix with # of links*	*Adjacency matrix*
Start to end date of facility	*CM1* *CM2* (decreasing)	*CM4*
Start date of facility	*CM3*	*CM5*

Table 1 Different centrality measures. The table summarizes the estimated five centrality measures that are based on the network matrix **M**. In CM1, CM2 and CM4 we consider the total number of facilities that *i* and *j* share in period *t*, for all *t* from the start date to the end date of each facility. In CM3 and CM5, we only consider the facility start date to define the link between two lenders. Further, CM1, CM2 and CM3 are based on the actual number (#) of links, whereas CM4 and CM5 are based on the adjacency matrix.

4.3 Explaining *ΔCoVaR*: the regression model

Market based econometric methods such as *ΔCoVaR* measure an individual firm's contribution to systemic risk but are mute about the firm-specific causes of systemic risk. To understand systemic risk from both an academic and regulatory perspective it is therefore useful to find the causes of systemic risk. We do so by using firm specific (accounting based) variables that can predict the systemic risk of a firm q quarters ahead. This is also done in Adrian and Brunnermeier (2016) and Brunnermeier et al. (2019). In contrast to these papers, we are primarily interested in investigating whether firm specific variables such as *VaR*, *NPL*, and *NII* vary in importance depending on the firm's centrality. That is, we not only investigate if centrality by itself contributes to systemic risk, but also if, for example, one unit of *VaR* contributes more to systemic risk for a firm that is centrally placed in the bank network. We do so by interacting centrality with previously found determinants of systemic risk.

We estimate panel regressions with year fixed effects and cluster standard errors on the firm level in all specifications. The most general specification (Model 1) is given by

$$\Delta CoVaR_{it} = \alpha_y + \boldsymbol{\beta}'\boldsymbol{X}_{\boldsymbol{i,t-1}} + \gamma CM_{i,t-1} + \boldsymbol{\psi}'\left(\boldsymbol{X}_{\boldsymbol{i,t-1}} \cdot CM_{i,t-1}\right) + \varepsilon_{it}, \tag{9}$$

with $\boldsymbol{X_{it}}$ being a $k \times 1$ vector of our firm-specific variables for firm i at quarter t, $CM_{i,t}$ being one of the six different centrality measures, α_y is a year fixed effect, $\boldsymbol{\beta}$ and $\boldsymbol{\psi}$ are $k \times 1$ coefficient vectors, and γ is a scalar. In the regressions, all variables are standardized to have a unit standard deviation to make the magnitudes of the coefficients directly comparable. Note that the almost prefect within-firm correlation between *VaR* and *ΔCoVaR* means it is not possible to estimate these panel regressions with firm fixed effects and simultaneously include *VaR* as an explanatory variable. Adrian and Brunnermeier (2016) include *VaR* and exclude firm fixed effects whereas Brunnermeier et al. (2019) exclude *VaR* but include firm fixed effects. Since we are interested in the effect of *VaR* and its interaction with centrality, we include *VaR* and exclude firm fixed effects.

5 Results and discussion

We start the analysis in Section 5.1 with the descriptive statistics of the variables used in the study. We then discuss the results of the multivariate regressions with the general specification (Equation 9) in Section 5.2. Section 5.3 investigates if the effects of the variables on *ΔCoVaR* are different in normal and recession periods. Finally, we analyze the role of size as a moderator variable in Section 5.4.

5.1 Descriptive statistics

The correlations among the variables are reported in Table 2. All variables are lagged one quarter in relation to *ΔCoVaR*. The values are time series averages from calculating a cross-sectional correlation each quarter. The correlations are in general very high between the first five measures, particularly between *CM1*, *CM2,* and *CM3*. We can conclude that using different facility durations to define the network has little effect on the relative importance of the lenders. The correlations between *CM6*, which is defined based on the number of facilities with the lead arranger role, and the other five measures, varies between 0.5 and 0.8. Interestingly all centrality measures are positively correlated with *ΔCoVaR* and size but negatively correlated with *VaR* with the exception of *CM6* which has a small positive correlation with *VaR*. Further, the correlation between size and centrality, while positive, is just around 0.2–0.3, depending on the centrality measure, indicating that size and centrality are distinct measures.

	ΔCoVaR	VaR	SIZE	LEV	NPL	NII	CM1	CM2	CM3	CM4	CM5	CM6
ΔCoVaR	1.00											
VaR	0.230	1.00										
SIZE	0.423	−0.156	1.00									
LEV	−0.007	0.198	0.068	1.00								
NPL	−0.053	0.339	−0.220	0.215	1.00							
NII	0.171	−0.037	0.381	−0.108	−0.046	1.00						
CM1	0.137	−0.036	0.251	0.011	−0.048	0.188	1.00					
CM2	0.142	−0.034	0.254	0.009	−0.039	0.188	0.967	1.00				
CM3	0.144	−0.032	0.252	0.007	−0.033	0.187	0.901	0.963	1.00			
CM4	0.179	−0.062	0.339	0.057	−0.072	0.278	0.714	0.685	0.644	1.00		
CM5	0.188	−0.045	0.293	0.024	−0.054	0.276	0.771	0.804	0.834	0.778	1.00	
CM6	0.115	0.009	0.195	−0.006	−0.017	0.083	0.792	0.774	0.713	0.489	0.560	1.00

Table 2 Correlation matrix. This table presents the correlations among all variables used in our analysis. All variables are lagged one quarter compared to ΔCoVaR. The correlations correspond to averages of cross-sectional correlations computed each quarter during the period 1995Q1–2016Q4.

Table 3 shows the summary statistics of the variables included in the regression analysis. The distribution of all the centrality measures, and in particular *CM6*, are skewed to the right with many firms having close to zero importance and a few lenders being very central. Only 8% of the lenders have *CM1* values equal to zero for all the periods (this is not shown in the table), which happens if they are the sole lender of a facility, while for *CM6*, 50% of the lenders have zero value over the entire period – they have never been the lead arranger of a facility – while 10 lenders led around 90% of the facilities in our sample. Citigroup and Bank of America led the largest average number of facilities, averaging 1,105 and 1,101 facilities, respectively. The most central firms based on *CM1* are, in general, the firms that often take the role as lead managers of facilities, but this is not always the case. For example, out of the 10 firms that have the highest *CM1* values, only six are top 10 leads.

	Mean	Median	Std. dev.	Kurtosis	Skewness
ΔCoVaR	0.032	0.031	0.020	9.839	1.551
VaR	0.114	0.099	0.060	13.779	3.079
SIZE	7.006	6.851	2.087	0.348	0.294
LEV	11.250	10.880	3.213	14.534	2.251
NPL	0.008	0.005	0.011	13.808	3.336
NII	0.358	0.250	0.447	29.923	4.952
CM1	0.012	0.000	0.046	35.936	5.573
CM2	0.013	0.000	0.050	35.111	5.563
CM3	0.012	0.000	0.050	36.088	5.635
CM4	0.009	0.000	0.022	11.089	3.305
CM5	0.011	0.000	0.033	12.110	3.538
CM6	51.179	0.000	324.625	131.770	10.459

Table 3 Descriptive statistics. This table presents descriptive statistics for all variables used in our analysis. Except for ΔcoVaR, all variables are lagged one period. Definitions and exact item identifiers of these variables are found in the appendix. The variables are on a quarterly basis and cover the period 1995Q1–2016Q4. The sample consists of 4,833 quarter–firm observations.

It is interesting to note that the mean value of *CM6* is 3.633 for the entire sample of 7,740 lenders (not reported in the table), and 51.179 for our sample. This shows that the firms included in our sample are, on average, more important than the excluded firms. More specifically, our selected sample of 264 lenders led 16% of the facilities in the total sample of 7,740 lenders. Our sample includes only 3% of the lenders used to construct the network, confirming the relative importance of the banks in our sample. This share has increased from around 8% (1995) to above 25% (2016). This increase is more apparent after the financial crisis. The increase depends partly on the selection of our sample (we use companies with at least 50 weeks of return data to estimate *ΔCoVaR*) and partly on the market becoming more concentrated, particularly after (and due to) the global financial crisis in 2008-2009.

Figure 1 illustrates a network matrix for the last quarter of our sample, 2016Q4. We use the adjacency matrix to avoid having several lines between any two nodes. We use the start and the end date of the facilities to construct this matrix. That is, two firms are assumed to be connected from the start date to the end date of each facility they share. Note that the figure only shows the links between the 264 firms used in our main study, while the centrality measures are based on the links between all 7,740 lenders. The figure shows that Citigroup, Bank of America, Wells Fargo, PNC Finance, and Northern Trust were each involved in many syndicated loans in this quarter.

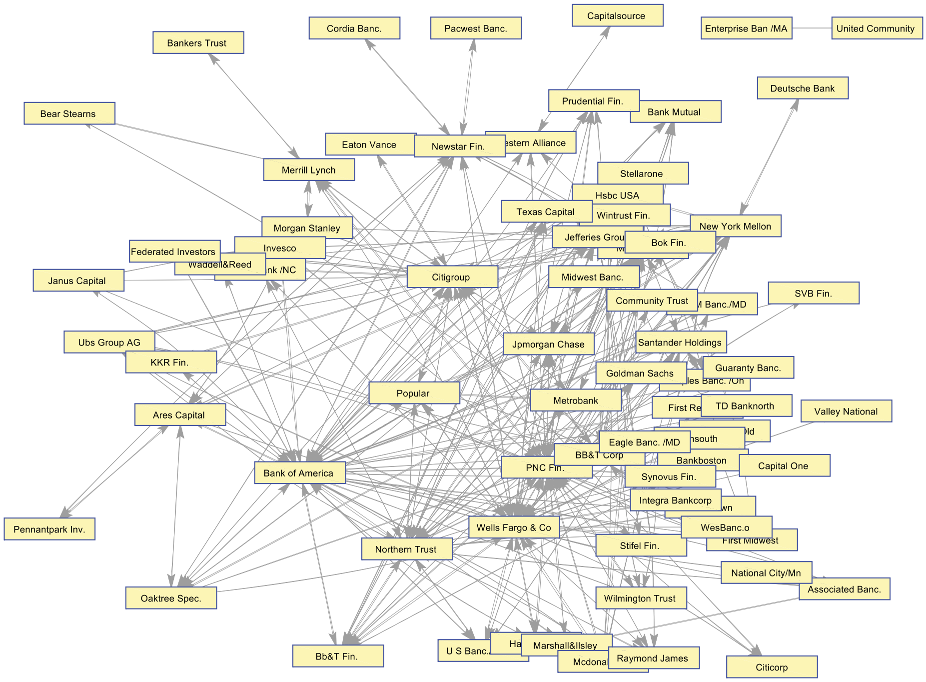


Figure 1 Network matrix. The figure shows the links between the 264 firms used in the main study, based on the adjacency network matrix for the last quarter of our sample, 2016Q4. Two firms are assumed to be connected from the start date to the end date of each facility they share.

In Figure 2, we show the persistency of centrality, the probability of belonging to the top 10% group in subsequent periods, as measured by our main centrality variable, *CM1*. We see that the probability of being central (being in top 10%) in two successive periods is quite high (mostly 90% to 100%). The values vary slightly for different periods. The probability that a firm belongs to the 10% most-central firms during the whole sample is just below 2%, which means that we should expect that around five firms belong to this group. In fact, the following four firms belong to top 10% *CM1* in all the 88 quarters: Citigroup, Merrill Lynch, Northern Trust and PNC Finance.

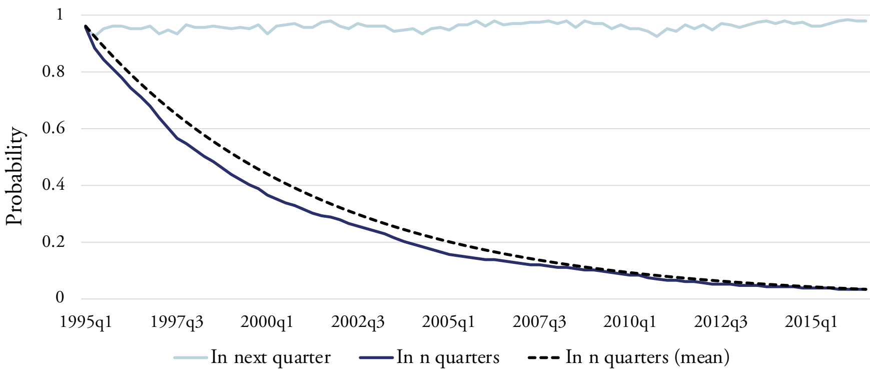


Figure 2 Persistency of centrality. The figure shows the probability of a bank remaining in the top 10% of CM1 values in the next quarter and in *n*-quarters, respectively, where *n* goes from 1995q1 to 2016q4 (1 to 88).

5.2 Regression results

Table 4 shows the results from regressing *ΔCoVaR* on all variables and their interactions with the centrality measure (Model 1, Equation 9). Note that, when an interaction term is included in the regression, it is no longer useful to interpret individual coefficients since the marginal effect of a change in the explanatory variable x_i is now given by

$$\frac{\partial \Delta CoVaR}{\partial x_i} = \beta_i + \psi_i CM \tag{10}$$

following equation (9). Since all regressors are standardized, the individual coefficients are to be interpreted as the change in *ΔCoVaR* for a one-standard-deviation increase in the variable when centrality is equal to zero. Similarly,

$$\frac{\partial \Delta CoVaR}{\partial CM} = \gamma + \psi_i x_i \tag{11}$$

which implies that the parameter γ is the marginal effect of centrality when the other risk factors are at zero. Therefore, the insignificance of this parameter for all of the different specifications in Table 4 indicates that the centrality of a firm does not induce systemic risk if the firm has a very low bankruptcy risk according to its other characteristics.

A very clear result from Table 4 is a positive and significant interaction effect between *VaR* and all measures of centrality. For our main measure of centrality, *CM1*, only *size*, *VaR,* and *centrality* appear to significantly affect *ΔCoVaR*. Size has a direct impact on *ΔCoVaR* whereas centrality primarily acts as a moderator variable, making the impact of *VaR* much more pronounced for centrally placed firms. The coefficients of the year fixed effects capture differences in *ΔCoVaR* over time that are not explained by any of the variables. These coefficients (not reported in the table) are not significantly different from zero except during the financial crisis in 2008–2009 and during 2010–2011.

	CM1	CM2	CM3	CM4	CM5	CM6
CM	−0.228	−0.206	−0.245	−0.032	0.109	−0.341
	(0.327)	*(0.327)*	*(0.338)*	*(0.406)*	*(0.373)*	*(0.351)*
VaR	0.122**	0.121*	0.119*	0.106*	0.119*	0.128**
	(0.062)	*(0.062)*	*(0.062)*	*(0.062)*	*(0.061)*	*(0.062)*
SIZE	0.516***	0.514***	0.511***	0.529***	0.505***	0.526***
	(0.094)	*(0.095)*	*(0.095)*	*(0.105)*	*(0.098)*	*(0.091)*
LEV	−0.021	−0.020	−0.021	−0.010	−0.018	−0.020
	(0.039)	*(0.039)*	*(0.039)*	*(0.040)*	*(0.039)*	*(0.038)*
NPL	−0.042	−0.043	−0.043	−0.047	−0.044	−0.044
	(0.039)	*(0.039)*	*(0.039)*	*(0.039)*	*(0.038)*	*(0.038)*
NII	0.009	0.016	0.014	−0.009	0.010	−0.008
	(0.046)	*(0.045)*	*(0.043)*	*(0.052)*	*(0.049)*	*(0.035)*
VaR×CM	0.163***	0.158***	0.160***	0.189***	0.169***	0.142*
	(0.040)	*(0.042)*	*(0.037)*	*(0.067)*	*(0.024)*	*(0.077)*
SIZE×CM	−0.017	−0.015	−0.009	−0.058	−0.061	−0.059
	(0.042)	*(0.042)*	*(0.043)*	*(0.058)*	*(0.056)*	*(0.050)*
LEV×CM	0.030	0.031	0.039	−0.021	−0.001	0.119
	(0.039)	*(0.040)*	*(0.042)*	*(0.043)*	*(0.036)*	*(0.098)*
NPL×CM	−0.029	−0.046*	−0.060**	0.064	−0.043	−0.051
	(0.032)	*(0.027)*	*(0.029)*	*(0.073)*	*(0.043)*	*(0.043)*
NII×CM	−0.016	−0.028	−0.029	0.015	−0.017	0.060
	(0.028)	*(0.027)*	*(0.025)*	*(0.017)*	*(0.017)*	*(0.066)*
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.42	0.42	0.42	0.42	0.43	0.42
n	4,780	4,780	4,780	4,780	4,780	4,780

Table 4 Regression of *ΔCoVaR* on all variables and their interactions with the centrality measure. The table shows the multivariate results when all variables and their interactions with the centrality measure are included simultaneously in the regression (Model 1, Equation 9). For the sake of comparison, we show the results for all the six different centrality measures. Definitions and exact item identifiers of the variables are given in the appendix. The variables are on a quarterly basis and cover the period 1995Q1–2016Q4. All variables are standardized to have unit standard deviation to make the magnitudes of the coefficients directly comparable. Standard errors clustered on the firm level are presented below the coefficient estimates. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Figure 3 shows the marginal effect of our five firm-specific variables on *ΔCoVaR* for different levels of centrality using *CM1*. The marginal effects of the variables *size* and *VaR* are positive and significant for all the possible values of *CM1*. For all the other variables, the marginal effect is always insignificant. Since the interaction effect is only significant for *VaR*, we will focus on the marginal effect of this variable for different levels of *CM1*. For the least-central firms, the effect of a one-standard deviation increase in *VaR* on *ΔCoVaR* is around 0.12. Each standard deviation increase in centrality increases this effect by 0.163. Thus for a firm two standard deviations more central than the minimum, the effect of *VaR* on *ΔCoVaR* is almost four times greater: $0.12 + 2 \times 0.163 = 0.446$. The results are generally very consistent between different measures of centrality.

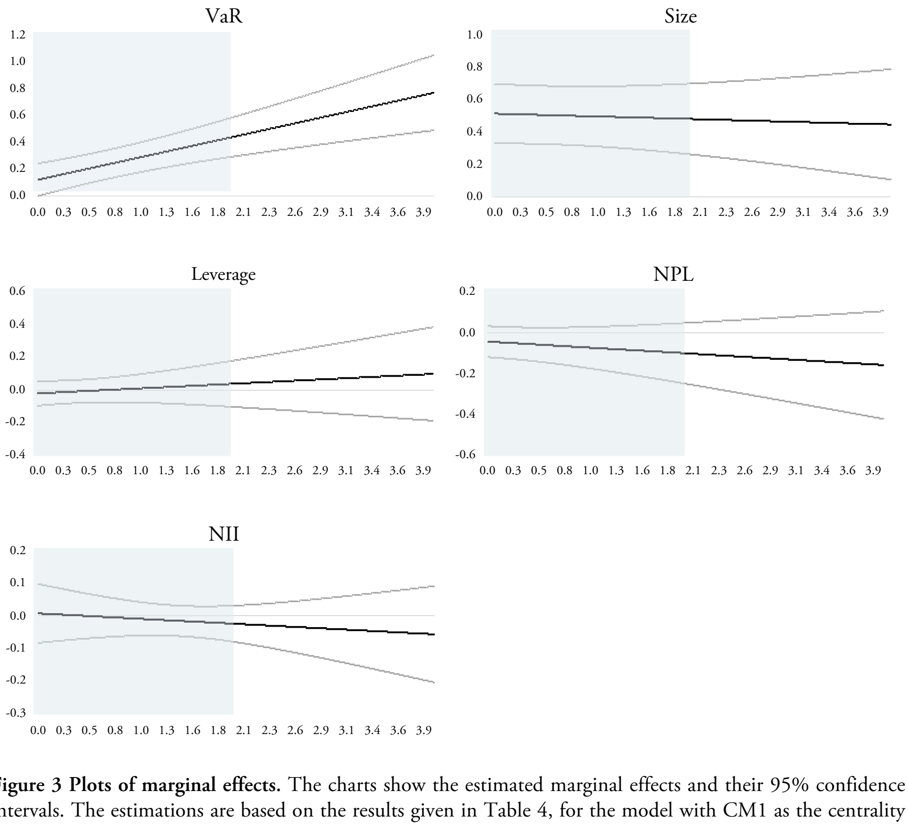


Figure 3 Plots of marginal effects. The charts show the estimated marginal effects and their 95% confidence intervals. The estimations are based on the results given in Table 4, for the model with CM1 as the centrality measure. In each figure, the y-axis shows the marginal effect of each factor on *ΔCoVaR* and the x-axis shows CM1 values. The shaded area shows the interval that contains 95% of the CM1 values.

Figure 4 shows the centrality and *VaR* of the 15 largest financial institutions in our sample as measured by market capitalization. Firms in the first quadrant have above average centrality and above average *VaR*; their contribution to systemic risk has previously been underestimated since the positive interaction between centrality and *VaR* is ignored. This is the case for Citigroup, Bank of America, and Morgan Stanley. Firms that have below average centrality and *VaR*, and hence have their contribution to systemic risk overestimated when ignoring interactions, include Goldman Sachs, Blackrock, and American Express. The firm with the highest *VaR* is Fannie Mae but its estimated contribution to *ΔCoVaR* is small since it also has the lowest centrality.

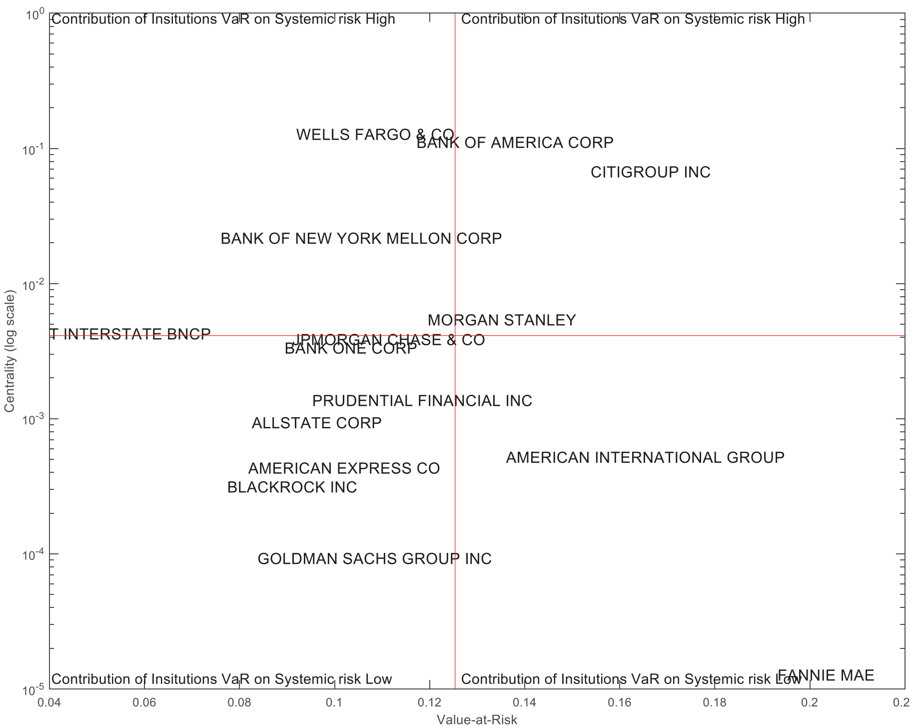


Figure 4 Coordinate map of centrality and Value-at-Risk. The figure shows the average centrality (over time) and average VaR for the 15 largest financial institutions in the sample in terms of market capitalization. The red lines show the (cross-sectional) average VaR and average centrality so that firms in the first (top right) quadrant have above-average centrality and above-average VaR.

5.3 The effect of recessions

In Table 5, we investigate how the results differ between recessions and normal times. We use two dummy variables in the regression, one for NBER recession periods[17] and one for normal (expansion) periods. All of the variables and their interactions are multiplied by these dummies. Overall, the direct effect of size becomes much more important during recessions, increasing from 0.46 to 0.83. Leverage has a positive and significant interaction with centrality during the normal periods, showing that this variable contributes more to systemic risk for centrally placed banks. Similarly, the interaction between *VaR* and centrality is highly significant during normal times. However, both leverage and *VaR* interacted with centrality, despite being larger during recessions, are insignificant, which indicates the imprecise estimates of these parameters during recessions.

During recessions there is also a significant, negative and large coefficient for the interaction between *NII* and centrality which is not present during normal times. The expected effect of *NII* on systemic risk is ambiguous. Brunnermeier et al. (2019) find that the systemic risk contribution is higher for banks with a higher level of *NII*. However, whether *NII* is beneficial or detrimental to individual firm risk has been studied with mixed results. For example, Fraser et al. (2002) conclude that a higher level of *NII* activities is related to more volatile returns, and De Jonghe (2010) finds that systemic risk increases monotonically with *NII*. *NII* is however also indicative of an overall diversification strategy of the firm and could therefore decrease systemic risk since it gives the firm a more diversified portfolio from other revenue-producing activities. However, banks with a low level of *NII* have more traditional business models and less proprietary trading and are, therefore, safer. Our results shed some light on the previously conflicted finding on the dual role of *NII* making a bank safer because of diversification benefits, but at the same time potentially riskier because of the risk of, for example, proprietary trading losses. We show that diversified banks (high *NII*) contribute less to systemic risk than other types of banks, but this difference only exists during recessions and only for centrally placed banks. Contrary to De Jonghe et al. (2015)

[17] The National Bureau of Economic Research (NBER) defines a recession very broadly as a "significant decline in economic activity spreading across the economy, lasting more than a few months". See NBER for more information. A recession is traditionally defined as a fall in GDP in two consecutive quarters.

and in agreement with Saunders et al. (2019), we do not find that *NII* reduces large banks' systemic risk contributions.

	Entire	Recession	Normal
Dummy		−0.608	−0.271
		(0.594)	*(0.388)*
CM1	−0.228	−0.171	−0.064
	(0.327)	*(1.281)*	*(0.200)*
VaR	0.122**	0.291***	0.119**
	(0.062)	*(0.070)*	*(0.060)*
SIZE	0.516***	0.830***	0.462***
	(0.094)	*(0.146)*	*(0.089)*
LEV	−0.021	−0.161*	−0.003
	(0.039)	*(0.083)*	*(0.034)*
NPL	−0.042	−0.051	0.022
	(0.039)	*(0.086)*	*(0.024)*
NII	0.009	0.036	0.001
	(0.046)	*(0.092)*	*(0.050)*
VaR×CM1	0.163***	0.126	0.103***
	(0.040)	*(0.104)*	*(0.032)*
SIZE×CM1	−0.017	−0.145	−0.046
	(0.042)	*(0.265)*	*(0.030)*
LEV×CM1	0.030	0.354	0.046**
	(0.039)	*(0.218)*	*(0.023)*
NPL×CM1	−0.029	0.661	0.020
	(0.032)	*(1.113)*	*(0.025)*
NII×CM1	−0.016	−0.551**	−0.009
	(0.028)	*(0.227)*	*(0.029)*

Table 5 Regression of *ΔCoVaR* on all variables and their interactions with the centrality measure during different periods. The table shows the multivariate results by separating recession and normal periods. We use two dummy variables in the regression, one for NBER recession periods and one for normal (expansion) periods. All of the variables and their interactions are multiplied by these dummies. Definitions and exact item identifiers of the variables are given in the appendix. The variables are sampled on a quarterly basis and cover the period 1995Q1–2016Q4. All variables are standardized to have unit standard deviation to make the magnitudes of the coefficients directly comparable. Standard errors clustered on the firm level are presented below the coefficient estimates. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

The marginal effects of the variables from this regression model are presented in Figure 5. The effect of *VaR* on *ΔCoVaR* is significantly positive, as well as increasing, for all levels of centrality, in both recessions and normal periods. The marginal effect of *size* is positive and significant for different levels of centrality, and it seems to be decreasing with increasing centrality. However, since the interaction term between *size* and *centrality* is insignificant in both periods (see Table 4), we can disregard the negative slope of the marginal effects of *size*. The marginal effect of *leverage* on *ΔCoVaR* is positive, but it is only significant during normal periods and for highly central firms. In contrast, *NII* has a negative and significant marginal effect on *ΔCoVaR* during recession periods. The effect is significant for all firms except those with very low *CM1* values.

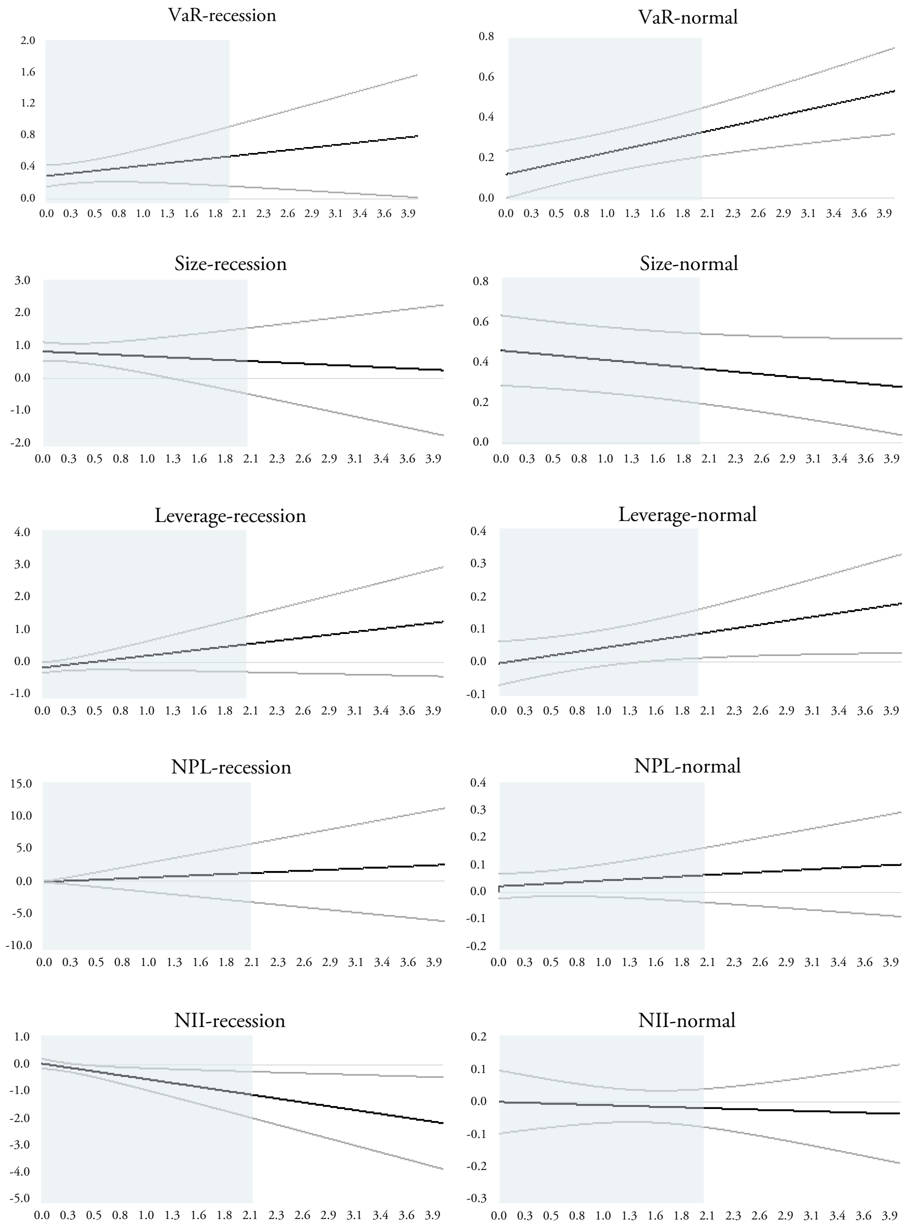


Figure 5 Plots of marginal effects during different periods. The charts show the estimated marginal effects for recessions and normal periods and their 95% confidence intervals. The estimates are based on the model in Table 5. In each figure, the y-axis shows the marginal effect of each variable on *ΔCoVaR* and the x-axis shows CM1 values. The shaded area shows the interval that contains 95% of the CM1 values.

The effect of *VaR* on *ΔCoVaR* is significant in both recessions and normal periods. To get a more detailed view of the relative importance of this variable over time, we use a multivariate regression model similar to that shown in Table 4, but we include a dummy variable for each year as a factor of both *CM1* and *VaR,* and with their interaction terms. We plot the marginal effects of *VaR* for different years in Figure 6. The marginal effect is generally higher during the financial crisis than other periods, but the difference is much more pronounced for centrally placed firms, as can be seen observing the z-axis in the three-dimensional space.

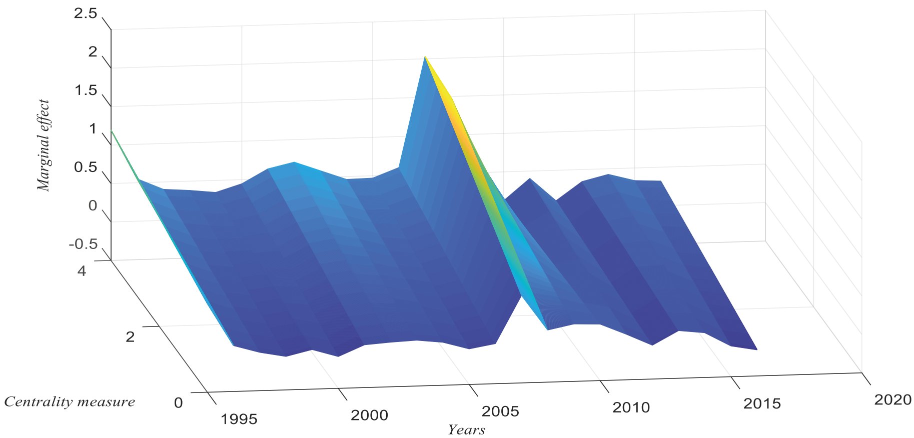


Figure 6 Plot of marginal effects in three dimensions. The figure shows the estimated marginal effect for different years. The estimates are based on a model with CM1 as the centrality measure, where we use a dummy variable for each year to estimate the yearly parameters of CM1, *VaR* and their interaction.

5.4 Size and centrality

As the correlation matrix (Table 2) showed, *size* and *centrality* of banks are related to each other. In Table 6, we investigate if *size* also has the role of a moderator variable for the effect of other bank specific variables, such as *VaR* and *leverage*, on systemic risk contributions. Model 1 in Table 6 is the same as in Table 4 but with only *CM1* as the centrality measure. In Model 2, we replace *centrality* with *size* in the interaction terms, and we include the interactions with both *size* and *centrality* in Model 3. The results show that *size* and *centrality* seem to work similarly; the effect of *VaR* on *ΔCoVaR* is much higher for large firms as evidenced by the significant interaction between *VaR* and *size*. This effect persists when we simultaneously allow for interactions with both *centrality* and *size* (Model 3).

	Model 1	Model 2	Model 3
CM	−0.228	0.239	−0.037
	(0.327)	*(0.154)*	*(0.327)*
VaR	0.122**	−0.258*	−0.220
	(0.062)	*(0.136)*	*(0.146)*
SIZE	0.516***	0.284*	0.309*
	(0.094)	*(0.173)*	*(0.186)*
LEV	−0.021	−0.007	−0.004
	(0.039)	*(0.103)*	*(0.107)*
NPL	−0.042	0.038	0.020
	(0.039)	*(0.107)*	*(0.114)*
NII	0.009	0.207	0.186
	(0.046)	*(0.196)*	*(0.203)*
VaR×CM	0.163***		0.083*
	(0.040)		*(0.049)*
SIZE×CM	−0.017	−0.042	−0.022
	(0.042)	*(0.028)*	*(0.042)*
LEV×CM	0.030		0.019
	(0.039)		*(0.044)*
NPL×CM	−0.029		−0.015
	(0.032)		*(0.039)*
NII×CM	−0.016		−0.010
	(0.028)		*(0.033)*
VaR×SIZE		0.134***	0.118***
		(0.038)	*(0.043)*
LEV×SIZE		0.004	0.002
		(0.031)	*(0.033)*
NPL×SIZE		−0.024	−0.017
		(0.038)	*(0.041)*
NII×SIZE		−0.045	−0.038
		(0.042)	*(0.046)*
Year dummy	Yes	Yes	Yes
Adj. R^2	0.42	0.43	0.44
n	4,780	4,780	4,780

Table 6 Regression of *ΔCoVaR* on all factors and their interactions with centrality and size. The table shows the regression results with *size* and *centrality* as moderator variables. Definitions and exact item identifiers of the variables are given in the appendix. Model 1 is from Table 4 with CM1 as the centrality measure. The variables are sampled on a quarterly basis and cover the period 1995Q1–2016Q4. All variables are standardized to have unit standard deviation to make the magnitudes of the coefficients directly comparable. Standard errors clustered on the firm level are presented below the coefficient estimates. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Although *size* and *centrality* are related, they do not capture the exact same information, as shown by the significant interaction between both *centrality* and

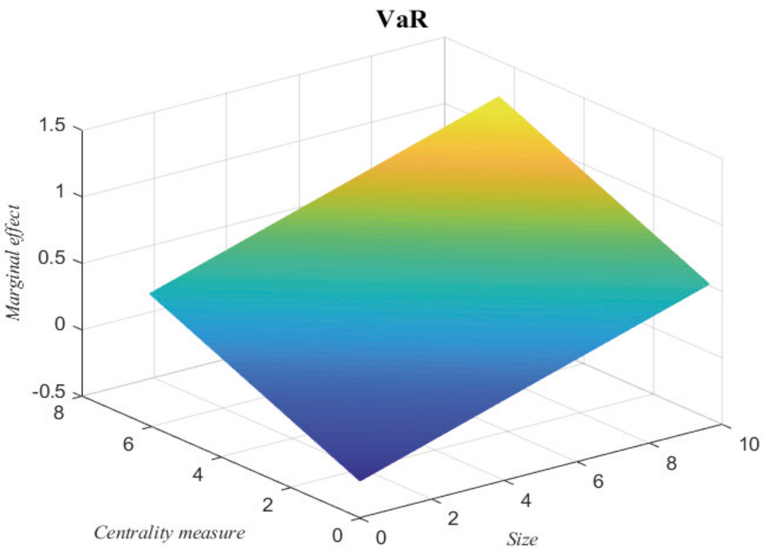
VaR , and *size* and *VaR*, when included simultaneously in Model 3. It should be noted that the marginal effect of the variables in Model 3 is

$$\frac{\partial \Delta CoVaR}{\partial x_i} = \beta_i + \psi_{i,CM} CM + \psi_{i,size} Size \tag{12}$$

Therefore, the insignificant coefficient of *VaR* in Model 3 suggests that firm-specific risk (*VaR*) of non-central and small banks (i.e. when *CM1* and *size* are close to zero) has no implication for systemic risk. Furthermore, since all the variables are standardized to have unit standard deviation, we can use the estimated parameters $\psi_{VaR,CM}$ and $\psi_{VaR,size}$ in Model 3 to directly compare the relative importance of *centrality* and *size* for the contribution of a company's *VaR* on systemic risk. The estimated parameters show that the effect of one standard deviation increase in *size* and *centrality* are of approximately equal magnitude (0.113 for *size* and 0.083 for *centrality*).

Figure 7 shows the marginal effect of the variable *VaR* for the multivariate Model 3 in Table 6, which includes the interaction of the variables with both *size* and *centrality*, with *CM1* as the centrality measure. Panel A gives the marginal effect when both *centrality* and *size* vary. The marginal effect when both size and *CM1* are in their minimum level is negative, while it raises to a value larger than 1 when both *size* and *CM1* are at their maximum values. In accordance with the results in Figure 7, the marginal effect increases more sharply with *size* than with the centrality measure. To give a better comparison of the relative impact of *size* and *centrality* on the marginal effect of *VaR*, and to be able to illustrate the confidence interval of the estimated marginal effect (Figure 7, Panel B), we plot the marginal effect of *VaR* by keeping one variable at its mean, while changing the other variable from its minimum to maximum values. The figure on the left shows that the marginal effect is significantly positive for all values of *CM1*, when *size* is fixed at its average level. However, when we fix *CM1* at its average value and vary *size* from its minimum to its maximum values, the marginal effect is only significant for banks with a *size* value above 2.7 (average *size* measure is 3.3). Therefore, a bank with average *centrality* can significantly affect systemic risk with its *VaR* only if the firm is not too small, while the *VaR* of an average-sized firm significantly affects systemic risk no matter how central the bank is. This comparison shows that *size* is a more important variable than *centrality* for transmission of individual risk to systemic risk. On the other hand, the figure on the left also confirms that, for an average sized firm, the marginal effect increases from around 0.22 to almost 0.50 as the *centrality* varies from its mean (0.25 is the mean of the standardized *CM1*) to its maximum level. This confirms that ignoring the impact of *centrality* will substantially underestimate the marginal effect of *VaR* on systemic risk.

A. Both *size* and *centrality* take different values



B. One of the variables is fixed at its mean level

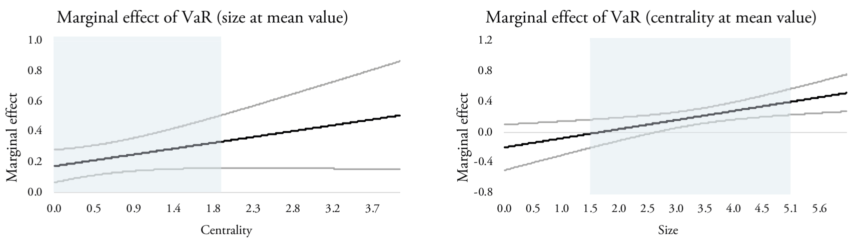


Figure 7A,B Plots of marignal effects. The figure in Panel A shows the estimated marginal effects of the variable *VaR* for different levels of bank *centrality* and *size*. The estimations are based on the multivariate regression model Model 3 in Table 6, which includes the interaction of the variables with both *size* and *centrality*, with CM1 as the centrality measure. In Panel A, both *size* and *centrality* measures take different values. In Panel B, we keep one variable at its mean value while changing the other variable. Panel B also shows the 95% confidence interval of the estimated marginal effects. The shaded area in each figure of Panel B shows the interval that contains 95% of the observations of the variable of the x-axis.

6 Conclusion

The aim of this paper is to examine if firm specific characteristics found to explain systemic risk matter more or matter less when firms' centrality is considered. Traditionally, firm characteristics' impact has been assumed to be independent of the firm's centrality, and current regulation of systemic risk treats centrality and firm-specific risk factors as separate sources of systemic risk. Our main finding is that centrality is an important determinant of systemic risk for all but the smallest banks, but not primarily by its direct effect. Rather, its main influence is as a moderator variable, making other firm-specific risk measures such as *VaR* and *NII* much more important for central banks. The effect is especially large for *VaR*, i.e. *VaR* is more important as an indicator of riskiness for an institution that is also highly interconnected, i.e. central in the network. A bank's contribution to systemic risk, as measured by *ΔCoVaR*, given *VaR*, is about four times higher for a bank with two standard deviations above average estimated network centrality, compared to a bank with average centrality. The effect is significant in both recessions and normal periods and is more pronounced the more central a bank is. Neglecting this indirect effect severely underestimates the importance of centrality for risky (high *VaR*) banks and overestimates the effect for safer banks. Our results also indicate the opposite; *VaR* of non-central and small banks has no, or very small, implication for systemic risk. Current regulation on systemic risk takes centrality into account since it is one of the five categories used for calculating systemic importance, but it does so as a standalone component. By giving each of the five categories that contribute to systemic risk equal weight, current regulation cannot capture that the importance of firm characteristics varies with centrality.

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Appendix

Variable definitions with identifiers

Variable	Definition
ΔCoVaR	The contribution to system *VaR* if a firm goes from being at its 50% *VaR* (normal state) to its 1 or 5 % *VaR* (distressed state).
VaR	The maximum expected loss that can occur during a given time period with probability *q*.
LEV	Total book assets [1007][18] divided by the book value of equity [1275]
SIZE	The natural logarithm of a firm's market capitalization [10054] in million USD.
NPL	Non-performing loans [3123] to total book assets [1007]
NII	Total noninterest income [27] to total interest income [25]
Change in the three-month yield	Three-month bill rate [H15/H15/RIFSGFSM03_N.WF][19]
Change in the slope of the yield curve	Yield spread between the 10-year treasury bill rate [H15/H15/RIFLGFCY10_N.WF] and the three-month bill rate [H15/H15/RIFSGFSM03_N.WF]
TED spread	Three-month LIBOR [USD3MTD156N] minus three-month bill rate [H15/H15/RIFSGFSM03_N.WF]
Change in credit spread	Change in the credit spread between Moody's Baa-rated bond yield [H15/discontinued/RIMLPBAAR_N.WF] and the 10-year treasury rate [H15/H15/RIFLGFCY10_N.WF]
Weekly market CRSP value weighted return	CRSP value-weighted market return
Weekly real estate sector return in excess of the market financial sector return	Average return of all firms with SIC codes 65–66 in excess of the financial market return. SIC codes starting with 6 except for the ones 65–66 are obtained from K. French Data Library[20]
Equity volatility	Rolling 22-day volatility of the weekly market CRSP value-weighted return

[18] Numbers in brackets refer to Compustat identifiers.
[19] Federal Reserve Bank of St. Louis, FRED Economic Database, https://fred.stlouisfed.org
[20] K. French Data Library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Implicit government guarantees and banks' stock returns

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Abstract

This paper investigates the effect of implicit government guarantees on equity returns by sorting financial institutions according to the systemic risk measures *ΔCoVaR* and the *marginal expected shortfall*, MES. In alignment with the risk-return trade off, riskier firms should earn higher expected returns. However, risky financial institutions also pose a threat to financial stability and can be considered *too-big-to-fail*. From this perspective it can be argued that the risk adjusted expected returns should be lower for highly systemic financial institutions than for less systemic institutions due to the loss absorbing capacity of the systemic institutions' tail risk by the government. Determining systemic importance from *ΔCoVaR* and MES, I find no evidence that points towards the perception that implicit government guarantees incurred lower risk-adjusted returns during the period 1987-2013.

Key words: systemic risk, too big to fail, bail-out, CoVaR, MES
JEL codes: G01, G12, G18, G21

1 Introduction

This paper focuses on the relationship between systemic risk and equity returns. I empirically investigate this relationship by i) *estimating* two systemic risk measures for a large sample of US bank holding companies, ii) *sorting* these financial institutions according to their level of systemic risk as implied by the measures, and iii) *analyzing* whether there are any equity return differences that can be attributed to institutions being different in terms of their systemic importance according to these measures, while controlling for other common risk factors. Why should we observe such a dispersion in equity returns? Systemically important institutions, that is, institutions that are considered essential to the effective and proper functioning of the financial system, are prone to government protection in the form of implicit guarantees. Implicit guarantees are a form of protection to these institutions that ultimately have a value in the form of lower funding costs. This implicit, or explicit, expectation of receiving such protection should ideally be visible in the market in the form of a lower risk premium, since it is a form of free protection that will reduce the risk of the institution in question. Institutions that make up such an important part of the financial system, such that they will be saved in case they were to go bust, are typically called *'too-big-to-fail'*. They are often big and they pose a risk to financial stability if faced with difficulties.

The global financial crisis of 2008-2009 shed light on the issue of implicit government guarantees for financial institutions. In the wake of the turmoil, especially following the collapse of Lehman Brothers in September 2008, governments tried to protect and safeguard financial stability by injecting large amounts of capital in order to support distressed banks. For example, the *Troubled Asset Relief Program* (TARP), announced by the U.S. Treasury at the peak of the crisis, has been considered the largest government bailout in U.S. history. One part of the program was the *Capital Purchase Program* (CPP), where around 700 banks received roughly USD200bn worth of capital injections from the U.S. Treasury. Ex post, these actions led to i.a. large banks growing even larger and banking sectors becoming more concentrated on a global level (IMF (2011)).

This paper takes its main methodological approach from Gandhi and Lustig (2015) (henceforth GL (2015)). They find that large (in terms of book and market value of assets) commercial banks' stocks have significantly lower risk-adjusted returns than small and medium sized banks' stocks, in spite of the fact that larger banks are more levered, i.e. risky. The difference is found not to be attributed to differences in standard risk exposures. GL (2015) argue that this resulting 'size premium'[21] is a compensation for financial crisis risk, i.e. compensation for being *too-big-to-fail* and systemically important. A systemic event can trigger a collective bail-out of larger banks but not of smaller (GL (2015)).

In my paper, I use the common systemic risk measures *ΔCoVaR* (Adrian and Brunnermeier (2016)) and marginal expected shortfall (MES, Brownlees and Engle (2012) and Acharya et al. (2017)), rather than book and market value of assets, to measure systemic risk and to determine systemically important financial institutions – the institutions most likely to be deemed *too-big-to-fail* by regulators, at least in theory. The link between systemic importance and equity returns is then analyzed by sorting firms into portfolios depending on their level of *ΔCoVaR* and MES at a certain time, and over time, following the methodology described in GL (2015). Implicit government guarantees are not measured directly in this paper, rather they are proxied for by examining whether there are return differences between highly systemic and less systemic banks, while controlling for common risk factors[22]. The hypothesis in GL (2015) postulates that the risk-adjusted return is expected to be lower in equilibrium for highly systemic banks, than for less systemic banks, due to the loss absorbing capacity of the systemic banks' tail risk by the government i.e. the highly systemic banks are simply *too big to fail*, or too *systemic* to fail, in the sense that their failure will have a severe impact on the functioning of the financial system, with negative consequences to the real economy, and the government will not allow this.

When a large bank defaults or is severely disrupted, the rest of the economy will suffer. There is hence an implicit expectation among market participants that when a large banking organization fails or is near failure, the government will, under most circumstances, intervene in order to prevent its complete failure and subsequent negative consequences for other parts of the economy. These

[21] The 'size premium', as originally presented in Banz (1981), stipulates that small stocks (as measured by market capitalization) yield, on average, significantly higher risk-adjusted returns than large stocks. This effect, that small stocks tend to outperform large stocks, is known as the size effect, or size premium.

[22] The analysis is carried out by estimating a factor model with five risk factors, following GL (2015). It is essentially the first part of the two-step procedure as presented in Fama and MacBeth (1973).

guarantees, or expectations, often imply significantly lower funding costs for the banks that benefit from them (Schich and Lindh (2012), Tsesmelidakis and Merton (2013)). We generally refer to these institutions as being systemically important. However, while *too-big-to-fail* implies that size is closely connected to systemic importance, this is not always the case. The *too-big-to-fail* terminology closely links systemic importance to size, but some banks and other financial institutions that are not particularly large, are still perceived as *too-big-to-fail* because of their essential role in the financial system. Examples of such institutions are clearing houses, mortgage institutions or highly connected, but relatively smaller, banks (Ennis and Malek (2005)). Also, size as such has not always been a unique criterion for bail-out policies[23]. Traditionally, interconnection and significant contagion effects have had a more central role (Kaufman (2014)). This justifies measuring systemic importance not solely with size, but with actual systemic risk measures that are broader in scope and take, among other things, interconnection into consideration.[24] This motivates the choice to use *ΔCoVaR* and MES in the analysis.

As long as the view that institutions that are deemed *too-big-to-fail* benefit from implicit government guarantees is upheld, investors and creditors may be incentivized to take on too much risk due to the fact that it will be the government, and ultimately tax payers, that will cover the bill in case of risk materialization, and not the institution itself. We call this moral hazard. There is hence also a belief that *too-big-to-fail* policies may generate a feedback mechanism, and indirectly cause problems that the policies should optimally contain in the first place (Boyd et al. (2009)). The perception of being *too-big-to-fail* also distorts competition in the banking sector in a way that small banks are less aided – big banks enjoy the implicit guarantee, small banks do not. The distortion may have negative consequences for the banking sector as a whole, as it promotes concentration and consolidation of businesses in the financial sector. Big firms are typically more diversified than small firms and are therefore put at a superior position when it comes to different types of exposures. Non-large banks would be

[23] Size is emphasized in the Dodd-Frank Act when determining systemic importance. It is not the only determinant but it is an important driver of systemic risk and often highly correlated with other characteristics that are important when determining systemic importance.
[24] The size of a bank, or a firm in general, can be measured in several ways and is, nevertheless, often a quick and easy way to define importance. The value of total assets (book or market) is the most frequently used definition of size among academics and policy makers.

incentivized to increase in size in order to be considered *too-big-to-fail* and hence becoming "eligible" for the advantage. This view is established in a number of studies e.g. Afonso et al. (2014) and Ueda and Weder di Mauro (2013), including one by IMF (2014) that concludes that banks may grow faster and larger than justified by economies of scale and scope only to enjoy the benefits from the implicit funding subsidy granted by the government. The IMF (2014) however states that expectations of implicit government interventions have decreased over time, but the probability of a systemically important institution being bailed-out still remains high.

My results do not indicate that implicit guarantees have an effect on the cost of equity of bank holding companies, i.e. I find no significant risk-adjusted return differences between sorted portfolios, even when controlling for standard risk factors. A possible explanation for this result would be that the government primarily benefits debt holders, rather than equity holders, when it intervenes during distress. Hence, the value, for shareholders, of implicit government guarantees is captured, *priced-in*, already in the standard risk factors. Alternatively, my results may also be driven by which institutions that investors really perceive to be *too-big-to-fail* rather than which institutions are, or should be in theory, *too-big-to-fail*. Since the guarantee is implicit, it is not always expected to be implemented. The possibility of a bail-out always exists but may be faced with credibility issues in reality which impacts the value assigned to it by investors (Acharya et al. (2016)). In addition, investors may of course solely use size as a proxy of *too-big-to-fail*, and rightfully so, since it is more easily observed than measures such as $\Delta CoVaR$ or MES that require some calculations. The "state of the art" when it comes to systemic risk measurement approaches, however, considers more than just size when estimating systemic importance. The question of whether and how implicit government guarantees are perceived by investors is nevertheless a purely empirical one.

This paper makes a contribution to the literature on systemic risk measurement among bank holding companies and to the empirical asset pricing literature by investigating the potential impact that these firms have on asset prices, due to them being systemically important. This is not the first paper to link implicit government guarantees to equity returns, however it is the first one to do so using an explicit measure of systemic risk in order to distinguish between firms that are most likely to benefit from implicit government guarantees. The remainder of the paper is structured as follows: section 2 reviews related literature on the topic as well as the paper of GL (2015) in more detail. Section 3 explains the concepts of systemic risk and implicit government guarantees, whereas section 4 and 5 review the methodology and data, respectively. Finally, section 6 presents the results and concludes.

2 Related literature

A very large body of literature has emerged on the topic of *too-big-to-fail* institutions as a result of the wide-spread attention that these institutions received in the aftermath of the global financial crisis. One of the first studies conducted on the topic of *too-big-to-fail* was, however, published two decades earlier, by O'Hara and Shaw (1990). In response to the US Comptroller of the Currency testimony, that the 11 largest banks in the US were *too big to fail* and should therefore be granted a total deposit insurance (Conover (1984)), O'Hara and Shaw (1990) investigate what effect this testimony has on bank equity values for the eleven largest banks and also for the banks that where implicitly named "too small to save". They find that the establishment of deposit insurance schemes strengthens the perception of *too-big-to-fail*; positive shareholder wealth effects are observed for the *too-big-to-fail* -deemed banks, but not for the non-included ones. For example, a 1.3 per cent rise in stock prices of the included banks was observed immediately after the information had reached the market. The magnitude of the wealth effects is also found to differ depending on e.g. bank size and solvency.

As observed in O'Hara and Shaw (1990), many studies show how banks that are allegedly deemed as *too-big-to-fail* enjoy benefits that non- *too-big-to-fail* banks do not. For example, Jacewitz and Pogach (2018) provide evidence of deposit rate advantages among the largest banks. They find that, during the crisis, the (comparable) risk premium paid by the largest banks was 35 basis points lower than the risk premium of other banks; this is consistent with a *too-big-to-fail* subsidy. The authors also show that the difference vanishes after the introduction of an increase in the deposit insurance limit. GAO[25] (2014) and Acharya et al. (2016) find that large banks' funding costs were lower than smaller counterparties before and during the financial crisis. Lester and Kumar (2014) find that bond

[25] US Government Accountability Office.

spreads of global systemically important banks (G-SIBs) were close to 100 basis points lower than bonds spreads of other banks in 2009. The IMF (2014) has further estimated *too-big-to-fail* subsidies in terms of funding cost advantages. They estimate that the subsidies made up at least 15 bps in the United States and 60-90 bps in the Euro area in 2012. In dollar terms, if applied to banks' total liabilities, these subsidies amount to approximately $15-$70bn in the United States, and $90-$300bn in the Euro area. Dávila and Walther (2019) explore how large and small banks make funding decisions in an environment with systemic bail-outs. They find that large banks always take on more leverage than their smaller counterparts because they know that their risk-taking will affect the government's optimal bail-out policies. They conclude that the size distribution of financial institutions matters for the ex-ante determination of leverage when bail-outs are possible.

Kelly et al. (2016) examine implicit government guarantees from an option pricing perspective and show that financial index put options remained relatively cheap during the great financial crisis. A put option is a type of derivate contract that protects equity holders in the case of price drops, and is therefore popular during times of distress because it provides a form of "crash insurance". Kelly and co-authors estimate that the price of "crash insurance" was surprisingly low during the 2007-2009 financial crisis, and more specifically that out-of-the-money put options for the index of financial stocks were "cheap" (69% cheaper in March 2009 compared to pre-crisis levels 2003-07) relative to out-of-the-money put options on the individual banks' equity that are included in the index. Kelly et al. (2016) hypothesize that the presence of a sector-wide bail-out guarantee is responsible for the spread between index put options and individual bank put options during the crisis. The price of crash insurance is lowered for the whole financial sector in anticipation of government intervention, but less so for individual banks. Since the government made investors believe that the industry would be financially safeguarded, demand for index put options was lowered, and drove down prices. The implicit promise of a bail-out hence served as a type of "free crash insurance" by the government, where the system as a whole would be protected, but where it would allow individual banks to fail. In this way, equity holders enjoyed a sizable government subsidy. The authors conclude by stating that equity and equity option prices are *"…contaminated by the government guarantee, and that this contamination can be dramatic"* (Kelly et al. (2016)).

Boyd et al. (2009) argue that the global financial crisis in 2008-2009 was mainly due to *too-big-to-fail* policies and governments' reluctance to let these institutions fail. They study the performance of a sample of the largest 25 US commercial banks, including Fannie Mae and Freddie Mac, and show that over the period 1986-2008 these institutions grew much faster than the rest of the banking sector and the US economy. Compared to the rest of the economy, and to other banks, these institutions' profits, asset size and market capitalization expanded massively. Largely, the literature has succeeded in presenting evidence in favour of the existence of bail-out expectations among investors and that these expectations have a pricing implication for assets, both debt and equity.

This paper is similar in spirit to that of Gandhi and Lustig (2015), I therefore spend some time reviewing their paper in more detail. Similar to this paper, they explore the asset pricing implications of systemically important firms, and show that the risk adjusted returns of the largest banks are lower due to implicit government guarantees that protect shareholders during crises. Systemic importance is determined through bank size, measured by both the book value of assets and market capitalization. The analysis is performed by first regressing monthly excess returns of commercial bank stocks for size-sorted portfolios (in deciles) on three common stock factors and two bonds factors, and thereafter confirming that the estimated intercepts are statistically significant and decrease monotonically with these sorted portfolios. Specifically, it is found that the intercept, *alpha*, of the tenth decile portfolio, based on market capitalization sorting, equals to -5.09 per cent (annualized, $p<0.01$). Further, it is also shown that a long-short position investing 1$ in the largest banks and shorting 1$ in the portfolio of the smallest banks loses 7.03 per cent ($p<0.05$) over the sample period 1970-2013. Similar results are also found when using book value to determine size.

The expected return gap between small and large banks grows bigger as the probability of recession increases. As an example, GL (2015) refers to the US, where larger banks were "much better off"; a total of 30 per cent of publicly traded commercial banks in the first size decile (the one tenth of banks that are the smallest) were de-listed, whereas there were no de-listings in the tenth size decile (the one tenth of banks that are the biggest). Connected to how Kelly et al. (2016) argue, GL (2015) suggest that government guarantees are seen as path-dependent put options that can only be exercised after large declines in a broad index of stocks and that this ultimately cuts off the left-hand tail of the large bank stock return distributions, but not so for small banks.

Based on the findings in the first step, GL (2015) apply principal component analysis to study the common variation in bank returns and find that the second principal component of risk-adjusted returns of size-sorted portfolios have loadings that depend monotonically on size; its loadings are positive for portfolios of small banks and negative on portfolios of large banks. This is the alleged procyclical 'size factor', or *size anomaly*, that measures bank-specific tail risk and that is orthogonal, i.e. independent, to standard risk factors explaining the cross-section of returns. Using the factor, i.e. the size portfolio that goes long in small bank stocks and short in long banks stocks, GL (2015) show that, per dollar invested, it loses an average of 41 cents during the first twelve months of NBER recession periods, controlling for standard stock and bond risk exposures. The implicit bank tail-risk premium, backed out by multiplying the loadings on the size factor by its markets risk price, further amounts to a 1.97 per cent lower expected equity return for the largest commercial banks' stocks, implying a large financial tail risk subsidy. To sum up, GL (2015) hence find results that indicate that large commercial banks in the US has lower risk-adjusted returns than smaller banks which supports the view that that implicit government guarantees for large banks are perceived by shareholders.

3 Systemic risk management in practice

3.1 Overview of regulation and supervision

In the words of the Bank for International Settlements[26], systemic risk is the risk that the inability of one or more participants to perform as expected will cause other participants to be unable to meet their obligations when due. From an economic perspective, it is when the impact of one or a sequence of events, has the potential to threaten the stability of the financial system, with effects that spread to the real economy. By threatening the stability of the system, it is meant

[26] The Bank for International Settlements (BIS) serves central banks in their pursuit of monetary and financial stability. The institution is often referred to as the bank of central banks.

that one or more of the system's core functions are impaired in a way that it has damaging effects also outside of the system. These core functions of the financial system are typically the three tasks that are of central importance for an economy to function and grow: to mediate an efficient payment system, to convert savings into funding and to manage different kinds of risks.

Many factors play a role when determining whether a financial institution is systemically important or not. For example, the Basel Committee on Banking Supervision (BCBS) together with the Financial Stability Board (FSB) identifies a list of globally systemically important banks, so called G-SIBs, yearly since 2012, where financial institutions are ranked according to their 'systemic importance'. Systemic importance is determined through an indicator-based approach where a score is calculated based on a set of indicators describing a certain aspect of systemic importance[27]. The thirty banks with the highest systemic risk score are subject to additional requirements. The list for 2019 and information about additional requirements are available in FSB (2019).

The Basel accords are a set of international standards and requirements imposed by the BCBS with the aim of promoting global financial stability by the harmonization of both bank regulation and supervision. In brief, the Basel Committee sets minimum standards for banking regulation and supervision which means that countries have to implement these standards at the minimum, but may implement stricter requirements should they want to. The Basel III framework is a third step in developing and improving these international standards. It tries to account for systemic risk specifically and to a larger extent by including, i.a. higher capital requirements for banks, increasing minimum liquidity levels, limiting maturity mismatch and imposing an explicit macroprudential stance through additional capital buffers[28] (BCBS (2014, 2018)). The aim of the regulation is to prevent financial institutions from taking on (excessive) risk in general, including systemic risk. The Basel Committee itself

[27] The sets of indicators are grouped into five categories that describe size, cross-jurisdictional activity, interconnectedness, substitutability/financial institution infrastructure, and complexity. Underlying these categories are twelve individual indicators that receive a weight when entering one of the five categories. For detailed information see the publication by BCBS, *Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement* (2018).

[28] E.g. the countercyclical capital buffer, capital conservation buffer and a systemic risk buffer aimed specifically at existing G-SIBs (see the list of G-SIBs complied by the FSB (2019)).

was created already in 1974, however, the mentioned regulatory additions (Basel III) are mainly a result of the global financial crisis in 2008-2009 that stressed the importance of more stringent regulation for banks.[29] Additionally, these developments are also underpinned by the academic research on systemic risk determinants and predictors that has emerged during the last decades. Moreover, national resolution and recovery plans[30] have gradually been introduced and improved over the years in order to lower the costs of bail-outs and their likelihood of occurring, by letting creditors and other agents know what they can expect in the case of failures (IMF (2014), European Commission (2014)).

Another aspect of supervision focuses on the interconnection, or network effect, between financial institutions and the mechanism of risk propagation between them (see e.g. Cai et al. (2018), Asgharian et al. (2019), Covi et al. (2019)). Risk spillovers among financial institutions and firms are a result of both direct linkages between them, e.g. in terms of interbank transactions for banks (Allen and Gale (2000)), and the commonality of asset holdings, in terms of holding assets with similar risk exposures (Cai et al. (2018)). Further, interconnection has long been recognized as an obvious channel of risk propagation. There is currently no specific regulatory aspect of this network characteristic present in the financial system. The 'systemic importance score' calculated by the BCBS[31], however, includes a component called 'interconnectedness', which involves three indicators; (i) intra-financial system assets; (ii) intra-financial system liabilities; and (iii) securities outstanding. Some of these balance sheet components are nevertheless not publicly available, which makes estimation hard or even impossible.

3.2 Bail-outs and implicit government guarantees

We already know that banks are special, but are systemically important banks perhaps even more special? And why should implicit government guarantees affect asset prices? When a financial institution fails, its failure will generate bankruptcy costs. Depending on the size and scope of these costs, a counterparty or third-

[29] For an overview and history of the Basel Committee and its accords see Niemeyer (2016).

[30] See Directive 2014/59/EU for the recovery and resolution of credit institutions and investment firms.

[31] See *Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement,* BCBS (2018).

party will have incentives to bail the firm out if bankruptcy threatens, in order to safeguard financial stability and avoid widespread economic damage. Such a third-party is typically a central bank or the government through the national debt office, which is the case in Sweden, for example. The implicit government guarantee hence involves the expectation of a bail-out, but without any explicit commitment of bailing out the firm (Kacperczyk and Schnabl (2011)). This element has market value. If a bail-out occurs then investors' expected losses are reduced and this ultimately affects the behaviour of banks. Banks will have little reason to limit risk-taking if there is a limit to downside risk by government guarantees (Forssbaeck and Nielsen (2015)). The resulting mispricing of risk induces moral hazard, in the sense that banks will engage in riskier behaviour without it being fully reflected in their cost of financing (Cordella et al. (2017)). This may be visible in, for example, reduced incentives to assure the quality of new loan originations and thus a deliberate increase in the risk level of new loans (Black and Hazelwood (2013)). An implicit government guarantee is hence a form of protection for *too-big-to-fail* financial institutions.

There are many examples of financial institutions being bailed out; the most eminent ones, and the ones we remember due to their scope, being the bail-outs occurring during, or right after, the 2008 financial crisis – the $29bn bail-out of Bear Stearns, the $85bn bail-out of AIG, the federal takeover of Freddie Mac and Fannie Mae in 2008, or even earlier, e.g. Continental Illinois in 1984, the savings and loan bailout of 1989, where more than a thousand savings and loans institutions defaulted, and LTCM[32] in 1998. The bail-outs during the 2008-2009 crisis were a result of the Emergency Economic Stabilization Act[33] (EESA) of 2008; a law that authorized the US Secretary of the Treasury to spend up to $700bn to buy distressed and toxic assets, and provide cash directly to banks. The Troubled Asset Relief Program (TARP) and the Capital Purchase Program (CPP), were both parts of the EESA. The CPP was allocated $250bns, where half of it was injected into the ten largest US banks through, mainly, purchases of preferred stock. Capital injections were limited in size to between 1 to 3 (later 5) per cent of risk weighted assets. The CPP later also opened up for "smaller" banks (<$500bn in total assets), but closed officially in December 2009, where a total of

[32] Long-term capital management L.P. was a hedge fund based in the United States.

[33] The Emergency Economic Stabilization Act of 2008 (Pub. Law No.:110-343). Proposed by Henry Paulson, passed and signed into law by President George W. Bush in October 2008.

$204.9bn had been injected into 707 financial institutions. Around 60 percent of the total amount was injected into the 19 largest banks. (Forssbaeck and Nielsen (2015)).

The overall effects of government support of banks in distress during the financial crisis of 2008-2009 are debated. On the one hand banks may be incentivized to engage in risk-shifting (Diamond and Rajan (2005), Farhi and Tirole (2012)), but on the other, government support in the form of capital injections may be necessary if the threat, or even materialization, of failure will jeopardize the stability of the financial system (Berger et al. (2020), Cordella and Yeyati (2003)). Big banks do also provide gains to the society in the form of economies of scale, cost synergies and lower funding costs for the whole economy. This is argued to justify implicit support (Packin (2015)). Generally, "safety nets" provided by governments and central banks in the form of, for example, deposit insurance or liquidity provisions, play a positive role and have a stabilizing force in preventing bank runs. Nevertheless, implicit government guarantees clearly raise a number of policy issues. Implicit government guarantees also directly imply a value transfer from tax payers to stakeholders of the financial institutions that enjoy the guarantees. (Moody's (2011), Schich and Lindh (2012)).

The *too-big-to-fail* principle is relevant to the financial sector, because it is here that we find the large and interconnected institutions that underpin the functioning of the economy. Banks, and other financial institutions, are indeed special, and different from other firms in other industries. Due to banks' ability to create money[34] and allocate financial resources among various market participants and sectors, they are seen to be "unique economic entities" (Palia and Porter (2003)). Banks are also vulnerable to bank runs, which makes them unique in that sense. A failing financial institution is typically very bad news for other financial institutions, whereas a failure in any other industry is typically good news for the remaining competitors as they may increase their share in the market. Bailing out financial institutions is hence generally seen as a problem; it is

[34] Banks can create *commercial bank money* by generating debt, which is different from central bank money. Bank lending, and therefore commercial bank money, is however restricted by laws and different regulations and its supply is not infinite. Central bank money is issued by the central bank and constitutes a claim on the state. Money issued by the state is considered to be completely safe as 100% of it is backed at all times. For an excellent review on the topic of money creation see e.g. *Money creation in the modern economy,* McLeay et al. (2014), Bank of England Quarterly Bulletin.

expensive, it gives rise to moral hazard and imposes a financial burden on tax payers.

4 Method

4.1 Estimating *ΔCoVaR*

ΔCoVaR is used as the main measure of an individual bank's systemic importance. I follow Adrian and Brunnermeier (2016) when estimating *ΔCoVaR* for each bank in the sample (the data is described in section 5). *CoVaR* is defined as the q%-VaR of an institution, conditional on another institution being in financial distress. Since I am interested in single banks' contribution to the systemic risk of the whole financial system, *CoVaR* is defined as the q%-VaR of the financial system, conditional on a single institution being in financial distress. The conditioning can also be reversed. The prefix *co-* is added to VaR to highlight the systemic nature – *conditional, comovement* or *contagion*, implying that there is more than one object involved and emphasizing the spillover characteristic (Adrian and Brunnermeier (2016)).

The *CoVaR* of the financial system thus measures what happens to a system's q%-VaR when another institution is in financial distress. *ΔCoVaR* instead answers the questions of how (much) the VaR of the system changes if a particular institution is in financial distress, or the other way around; how the VaR of a single institution changes should the system be distressed. Or in different words, the tail risk contribution of each firm, where the tail risk is the risk of an equity loss that is larger than a pre-specified threshold, with a pre-specified probability and over a pre-specified time period. The idea behind *CoVaR* comes from the fact that the distribution of asset values of the financial system is dependent on the overall health of all the individual institutions and their synchronicity. Hence, *CoVaR* estimates the size of the system distribution tail of asset values and how it changes should an individual institution experience financial distress (Adrian and Brunnermeier (2016)).

The twofold dimension inherent in the estimation of *CoVaR* and *ΔCoVaR* requires a conditioning event, call it $\mathbb{C}(X^i)$. This is usually set to the conditioning (distressed) object having reached its 1% or 5%-VaR level return (typically a loss), or more. In the paper I estimate the *ΔCoVaR* of the financial system, given that a single institution is distressed, with distress meaning 1%-VaR[35]. The equations below present the idea (originating in VaR) and calculation of the contribution of firm *i* to the systemic risk of the financial system *j*.

$$\Delta CoVaR_q^{j|\mathbb{C}(X^i)} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{q=0.5}^i} \tag{1}$$

$$Pr\left(X^j \leq -CoVaR_q^{j|\mathbb{C}(X^i)} \middle| \mathbb{C}(X^i)\right) = q$$

$$Pr\left(X^i \leq -VaR_q^i\right) = q$$

Econometrically, the above variables are estimated through quantile regressions. First, the relationship between *i* and *j* is estimated at the quantile of interest (e.g. the 1st quantile (0.01), using a rolling window of two years

$$X_t^j = \alpha_{t,j} + \beta_{t,q}^j X_t^i + \varepsilon_t \tag{2}$$

Second, the estimated vector of $\hat{\beta}_q^j$ coefficients is used to calculate $CoVaR_q^{j|X^i=VaR_q^i}$ in the following way

$$CoVaR_{t,q}^{j|i} = \hat{\alpha}_{t,j} + \hat{\beta}_{t,q}^j VaR_t^{i,q\%} \tag{3}$$

Finally, since I am interested in how much *more* risk is passed on to the system given that an institution is in distress (or the other way around), we draw on the estimated relationship between *i* and *j* in the left tail (q=0.01) and calculate $\Delta CoVaR_q^{j|\mathbb{C}(X^i)}$ as follows

$$\Delta CoVaR_{t,q}^{j|\mathbb{C}(X^i)} = \hat{\beta}_q^j\left(VaR_t^{i,q\%} - VaR_t^{i,50\%}\right) \tag{4}$$

Firms that are systemically important will have a higher (in absolute value) $\Delta CoVaR_q^{j|\mathbb{C}(X^i)}$. One can also express the *ΔCoVaR* measure in dollar terms in order to relate it to bank size, measured here as the book value of total assets:

$$\Delta\$CoVaR_{t,q}^{j|\mathbb{C}(X^i)} = {}^{\$}Size^i \cdot \Delta CoVaR_{t,q}^{j|\mathbb{C}(X^i)} \tag{5}$$

[35] The 5% estimations are executed as a part of the sensitivity analyses. See the appendix for more results.

$\$\Delta CoVaR$ now measures the change in dollar amounts as institution i goes into distress, i.e. the dollar value of the distress, the monetary expected loss.

4.2 Estimating the Marginal expected shortfall

In addition to $\Delta CoVaR$, I also use a different measure. Described by Brownlees and Engle (2012) and Acharya et al. (2017), the *Marginal Expected Shortfall* (MES) defines the expected equity loss of a firm in a crisis. The equity loss is predicted by the expected equity loss of firm i if market returns fall below a specified threshold over a given time horizon (Brownlees and Engle (2010)). The threshold is normally set to either -2% or simply the estimated 1% 1-day VaR of the market (which is often around -2 %). Hence, MES, also denoted as the short run MES in the original manuscript, is defined as the expected one-day return of a firm i given a one-day market decline of 2%.

$$MES_t^{i|j} = -E_{t-1}\left[r_t^i \middle| r_t^j \leq -VaR_t^{j,q}\right] \tag{6}$$

$$MES_t^{i|j} = -\frac{1}{\#\,days} \cdot \sum_{\substack{t:market\ return \\ in\ 1\%\ worst\ days}} r_t^i$$

Ultimately, it calculates the average return of the firm, $E\left[r_t^i\right]$, for those days that the market return is less than its q%-VaR, or when the loss is greater than or equal to 2%, depending on which definition of a market loss is chosen. I find the 1%[36] worst days for the market, and compute the firm's return on these days.

The MES has its origin in the ES, *expected shortfall*, of the market j, formally defined as

$$ES_t^j = -E_{t-1}\left[r_t^j \middle| r_t^j \leq -VaR_t^q\right] \tag{7}$$

The *expected shortfall* is the expected return of the market, given that the market already has a return that is lower than its VaR. In other words, the expected loss should the VaR be reached or more. To understand the intuition behind MES we decompose the market return, r_t^j, into the sum of its components' returns, r_t^i, so that $r_t^j = \sum_i y_t^i r_t^j$, where y_t^i corresponds to the weight of each firm i in a (universal) portfolio. We can now rewrite the expression for ES_t^j as follows

[36] 5% estimations are executed as a part of the sensitivity analysis.

$$ES_t^j = -\sum_i y_t^i \, E_{t-1}\left[r_t^j \middle| r_t^j \leq -VaR_t^q\right] \tag{8}$$

Differentiating the above expression with respect to each weight y_t^i we obtain the MES for the institution *i:*

$$\frac{\partial ES_t^j}{\partial y_t^i} = E_{t-1}\left[r_t^i \middle| r_t^j \leq -VaR_t^{j,q}\right] \equiv MES_t^{i|j} \tag{9}$$

In this context, we interpret MES as how much firm *i*'s risk-taking adds to the market's overall risk, the *marginal* expected shortfall.

Similar to $\Delta CoVaR$, the conditioning event in MES is defined as the market being on or below its q%-VaR, i.e. a percentile in the left tail of the return distribution. The intuition for MES for being a systemic risk measure is that if a firm *i* is linked to a systemic event it should be visible in its expected conditional return. Firms that are systemically important will have a higher (in absolute value) MES.

Several measures of systemic risk have emerged during the last decades[37], both in the academic literature and among practitioners, but there is still no agreement upon what exactly is being measured. It is recognized that systemic importance is derived from systemic risk, but systemic risk in turn is a multifaceted phenomenon that has its origin in many sources and may spread through various channels, thus making it hard to dissect. A common problem when dealing with systemic risk measures is furthermore that they often do not give a consistent ranking of systemically important institutions. The ranking is consistent over time within each measure, but often not in between measures. This issue is brought up and investigated empirically and theoretically by Benoit et al. (2013) and in Acharya et al. (2012). In the latter, the authors show that $\Delta CoVaR$ will treat two firms as identical, from a systemic point of view, if their return correlation with

[37] The most well-known and well-used systemic risk measures are $\Delta CoVaR$, MES and SRISK. As opposed to $\Delta CoVaR$ and MES, which are fully market-based measures, SRISK is a hybrid, drawing on both market data and balance sheet inputs. SRISK measures the expected capital shortfall of a financial institution relative a capital requirement of k% of assets (usually 8%), and given that the market falls by 40 % or more, during a consecutive period of 6 months (see Brownlees and Engle (2017), for the derivation of the full SRISK formula). The financial institution with the largest capital shortfall is considered as most systemic. SRISK is not calculated here as it cannot be meaningfully applied to small, or even mid-size, institutions.

the market is the same, despite of the fact that they might have different return volatilities. Benoit et al. (2013) show that there is a high level of similarity between MES and *ΔCoVaR* in terms of ranking, with an average percentage of concordant pairs of 43 %. They also find that the systemic risk measures deliver a consistent ranking for a given institution over time. For this reason, and for robustness, it is important to consider not only one systemic risk measure, but optimally several when determining systemic importance among financial institutions.

5 Data and model specification

The analysis in this paper is centred around publicly traded financial institutions in the US and their equity prices. All equity series are daily closing values in USD and returns are calculated by taking the difference of log prices from day *t-1* to *t,* as per usual. The equity price data is obtained from the CRSP-Compustat database and covers publicly traded bank holding companies with SIC code starting with 60, or historical SIC code 6712. The sample begins in January 1985 and ends in December 2013, and the corresponding estimations of *ΔCoVaR* and MES begin in January 1987 and end in December 2013. The sample of firms is originally the same as that used by GL (2015), including the corrections that they make.[38] As stated by GL (2015), the SIC definition above ensures that bank holding companies are included in the sample. Even though the main interest lies in commercial banks, bank holding companies need to be included because some banks, that belong to a holding company, are not publicly traded. They also bring up the issue that there is no well-identified way to classify US commercial banks in CRSP, which is why some banks are added manually after the automated compilation.

As of June 2020, there are approximately 5,000 FDIC insured commercial banks and savings institutions in the US. This number has declined since the beginning of the 2000's when it was approximately the double. During the same time, the total value of assets of these institutions has on the other hand increased to more than double; from around USD7,500bn to USD21,000bn. Only a small fraction, around 13%, of these institutions are publicly traded. The final sample is hence

[38] As stated in GL (2015), several of the largest US banks drop out of the sample. They are added manually.

an unbalanced panel set of roughly 100,000 stock months covering around 600 banks in total, over the whole sample period.

As described in more detail in section 5.2, I estimate a Fama-French (1993) five factor model. The input variables for the regressions are Fama and French's first three factors (Fama and French (1993) as well as two additional bond factors[39] and they are obtained from the dataset provided by GL (2015). The data provided by the authors covers the time period 1985-2013; for replicative and comparative purposes I choose the same observation period. *ΔCoVaR* and MES are estimated for all firms in the sample, every month, using quantile regressions (for *ΔCoVaR)* based on daily data during the period January 1987 to December 2013. The market return is proxied by the S&P500 Financials index. However, only stocks (institutions) that have both an estimated MES and *ΔCoVaR* measure are included in the final data sample. For this reason, the sample used in this paper is not unerringly the same as the sample in GL (2015). However, it is sufficiently similar as I manage to replicate the results of GL (2015) using size (proxied by market capitalization and the book value of assets) to distinguish between *too-big-to-fail* institutions[40]. My final sample is hence enough to represent the universe of listed bank holding companies in the US.

A possible limitation of the sample is the fact that it only covers a time period up to 2013[41]. For example, Berndt, Duffie and Zhu (2018) estimate "*a major decline in too-big-to-fail*", i.e. a significant decrease in the bail-out probability of (large) US banks post the financial crisis of 2008-2009. Since the crisis, there have also been developments in insolvency laws and banks resolution regimes worldwide that make bail-outs harder to implement.[42]

39 See the model specification in section 5.2.
40 Table 1 in GL (2015).
41 This is to have directly comparable results to GL (2015).
42 For example, introduction of tools such as bailing-in the creditor, rather than a tax-payer funded bail-out.

5.1 Portfolio construction

The simplest way to assess whether there are return differences between different firms, which could be explained by some characteristic, is to compare these firms' risk-adjusted returns based on this characteristic. After estimating *ΔCoVaR*, *Δ$CoVaR* and MES for all banks in my sample I therefore, mid-monthly, sort the banks' stocks into different groups depending on their estimated level of systemic risk as implied by these measures. These groups are treated as portfolios whose corresponding value-weighted excess returns are calculated and regressed on a set of standard controlling characteristics that are known to explain return differentials[43]. Finally, I am interested in the "*alpha*", which will represent the return in excess of what is already due to the included risk factors, and hence an indication of the existence of a return differential between systemic and non-systemic firms (as measured by *ΔCoVaR*, *Δ$CoVaR* and MES). In this paper, I am specifically interested in the possible return differential between the most systemic firms, and the least systemic firms. The highly systemic firms are most likely to receive government support in times of severe crisis, whereas the systemically "unimportant" firms are unlikely to receive such support. Due to this fact, and if it is perceived in the market, investors should require a smaller risk premium for the most systemic financial institutions, and a higher one for the least systemic institutions, all else equal.

Portfolios are constructed each month. 15 portfolios are constructed in total, for each measure. The first 10 portfolios represent deciles, updated each month, where firms are sorted according to their level of *CoVaR*, *Δ$CoVaR* and MES level mid-month throughout the sample period. The return of the portfolio represents the value-weighted return of each firm included that month. For example, the first portfolio, or the first decile, represents the value-weighted returns of a portfolio that is long bank stocks that are categorized into the lowest systemic risk decile in a specific month. The tenth decile then represents the value-weighted returns of a portfolio that is long bank stocks categorized into the highest systemic risk bucket, i.e. one tenth of banks that have the highest systemic risk as measured by the systemic risk measures that month. Systemic risk is increasing in portfolio number for all measures, so the higher the portfolio number the higher the systemic risk estimated.

[43] Such as for example the three well-known Fama-French factors.

Following GL (2015), the tenth bucket is further divided into buckets 10A and 10B. Portfolio 10A consists of the portfolio return of the lower half of the 10^{th} decile, and 10B consists of the upper half. This is done due to the fact that there are a few extremely (in relation to the rest) systemic firms that may skew the 10^{th} portfolio characteristics. The effect of these highly systemic firms is better studied if separated.

On top of these 12 portfolios, I also construct three additional ones representing zero-investment strategies. The first one (called portfolio "10-1" meaning "10^{th} portfolio minus 1^{st} portfolio") represents the 10^{th} portfolio's returns in excess of the smallest portfolio's return; that is, a portfolio that is long stocks that are sorted into being highly systemic, and short stocks that belong to the least systemic group of firms. In the same way, we also construct two portfolios for each half of the 10^{th} portfolio buckets, portfolios "10A-1" and "10B-1". The construction of all portfolios follows GL (2015).

5.2 Model specification

The value-weighted excess returns of the portfolios previously described are regressed on the three Fama-French risk factors and two additional bond risk factors. The standard Fama-French factors are the *market return* in excess of the risk-free rate, the *size factor* representing a portfolio that mimics monthly return differences between the smallest and the biggest firms, and the *value factor*, representing a portfolio that mimics return differentials between firms with high and low book-to-market-ratios. The bond factors are *ltg*, denoting the excess returns on an index of 10-year government bonds issued by the U.S. Treasury, and *crd*, denoting the excess returns on an index of investment grade 5-year corporate bonds. The *ltg* factor represents a measure of interest-rate sensitivity resulting from the maturity mismatch between assets and liabilities. The factor can be said to largely measure business cycle risk. The *crd* instead represents firms' potential exposure to (corporate) credit risk and therefore essentially the riskiness of bank assets overall. These additional factors are included because banks typically hold bonds of different maturities and risk in their portfolios and serve as the primary source of funding to the corporate sector. The equation below is estimated for all portfolios 1 to 10, 10A, 10B and for the zero-investment strategies.

$$R_t^p - R_t^f = r_t^p = \alpha^p + \boldsymbol{\beta^{p}}'\boldsymbol{f_t} + \varepsilon_t^p \tag{10}$$
$$\boldsymbol{f_t} = [mkt\ smb\ hml\ ltg\ crd]$$

The term on the left-hand side, $R_t^p - R_t^f$, represents the return of the portfolio, r_t^p, in excess of the risk-free rate, R_t^f. R_t^p represents the monthly return on the p^{th} *CoVaR*, *Δ$CoVaR* or MES sorted portfolio. $\boldsymbol{\beta^p}$ represents the vector of factor betas and α^p is meant to capture the risk-adjusted excess return, the risk premium, if it subsists. The five factors are contained in the vector $\boldsymbol{f_t}$.

6 Results

6.1 Descriptive statistics of formed portfolios

Table 1 presents average values of all of the portfolios, according to the sorting variable, i.e. the systemic risk measures. The first row (1987-2013) represents the whole sample period and the second row covers the financial crisis period (here broadly defined as between 2007-2010[44]). The stocks that have the lowest value for the systemic risk measures are put in the first group, and so on. Further, group 10 is split in two halves, 10A and 10B, as described in the previous section.

Portfolio	1	2	3	4	5	6	7	8	9	10	10A	10B
Average 1%-ΔCoVaR												
1987-2013	-0.20%	0.75%	1.21%	1.56%	1.90%	2.27%	2.71%	3.26%	3.84%	4.96%	4.52%	5.38%
2007-2010	-0.82%	0.40%	1.10%	1.53%	1.94%	2.50%	3.12%	3.84%	4.68%	6.42%	5.66%	7.15%
Average 1%-Δ$CoVaR (in million USD)												
1987-2013	0.07	0.25	0.80	1.43	2.73	5.15	9.94	22.93	69.73	1587.1	234.9	2882.1
2007-2010	0.00	0.11	0.43	0.80	1.30	2.30	4.76	11.56	35.20	2425.4	116.7	4649.5
Average 1%-MES												
1987-2013	-1.17%	-0.03%	0.27%	0.54%	0.82%	1.12%	1.49%	2.00%	2.75%	4.56%	3.70%	5.40%
2007-2010	-0.74%	0.04%	0.30%	0.60%	0.88%	1.26%	1.81%	2.47%	3.25%	4.89%	4.14%	5.61%

Table 1 Average systemic risk of portfolios. The table presents average values of the sorting variable, 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES, for different portfolios. The first portfolio consists of firms that have the lowest level of the mentioned measures, and the 10th portfolio consists of firms that have the highest level of the mentioned measures. Note that the values are inverted; CoVaR and MES are losses. A negative value in the above table (such as for example in portfolio 1) hence represents a gain, i.e. a positive contribution to market wide stress ("decreasing" stress). Sortings are executed each month, firms may therefore jump in between portfolios at different periods in time. See Table 3 for transition probabilities.

[44] There are no agreed upon exact dates for when the crisis started and ended. The crisis period is defined to illustrate a distressed period, and no results are executed based on that period only.

Table 1 gives an indication of the range of the systemic risk measures between different portfolios. We start by noticing that values are increasing as we move from left to right. This is per construction, because firms are sorted into deciles depending on what level of 1%- $\Delta CoVaR$, 1%-$\Delta\$CoVaR$ and 1%-MES they have. The first portfolio contains the firms that have the lowest level of systemic risk, as estimated by the measures, in each month throughout the sample period. Stocks may be placed in different deciles at different points in time. What can also be observed in the Table is that the increase, when moving from left to right, is not linear. The first portfolio of firms has an average value of 1%-$\Delta CoVaR$ of -0.2%. Since our numbers are expressed in terms of losses, a negative number means a gain. In this case it means that the least systemic firms in fact have a positive impact on market tail risk (expressed as VaR), on average, in stressful market conditions, i.e. the VaR of the system gets smaller. The most systemic financial institutions, group 10, instead have an average 1%-$\Delta CoVaR$ of about 5%, which is 25 times bigger than the firms in group 1.

Another interesting angle is to look at the average $\Delta\$CoVaR$ which expresses the capital shortfall in million dollars. In $\Delta\$CoVaR$, the estimated capital shortfall $\Delta CoVaR$ is put in relation to the size of the bank by multiplying by its total assets (book value). Comparing only the 9th portfolio with the 10th portfolio we see a difference of about 1.5 billion dollars. This difference is huge taking into account that these portfolios are conjoining. When portfolio 10 is further divided into 10A and 10B, the size dispersion is even more obvious. The difference in observed 1%-$\Delta CoVaR$ and 1%-MES values of the corresponding portfolios is much smaller. One also observes that the values are larger (in absolute value) when looking at the years 2007-2010, compared to the full sample period. This is as expected. The crisis period was a stressful time for financial institutions and equity returns reflected these market conditions accordingly. It can also be noted, looking at $\Delta\$CoVaR$ values, that $\Delta\$CoVaR$ was smaller for almost all portfolios except for portfolio 10, and specifically for portfolio 10B where the expected average "value at risk" was almost twice as large as the average during the whole sample period. This indicates that the financial institutions that are systemically very important are indeed also probably very large, in terms of the scope of their assets.

Table 2 presents average returns of systemic risk-sorted bank stocks; we take the portfolio groupings in Table 1, and calculate value-weighted average returns for each portfolio, each month, then averaging over the sample period. No systematic pattern in the average risk adjusted returns over the whole sample period is observed clearly. For *ΔCoVaR*-sorted bank stocks, portfolio 10B has the highest average historical return (1.39%), and portfolio 1 the lowest (0.34%). The range of returns for the rest of the portfolios varies, as can be seen more clearly in Figures 1-4. Also as expected, average returns are negative for all systemic risk measures during the crisis period 2007-2010. However, we do observe a pattern in the 1%-*ΔCoVaR* sorting where firms that were less systemic had, on average, a lower return than relatively more systemic firms, almost for all portfolios. This is not as obvious in the sorting based on MES and *Δ$CoVaR*. A general conclusion from this type of purely numerical analysis without any statistical inference is however still that less systemic banks seemed to be hurt more (in terms of equity losses) than relatively more systemic firms, at least during the great financial crisis period.

Portfolio	1	2	3	4	5	6	7	8	9	10	10A	10B
Average returns of 1%-ΔCoVaR sorted portfolios												
1987-2013	0.34%	0.89%	1.19%	0.90%	0.73%	0.66%	0.88%	0.80%	1.20%	0.94%	0.73%	1.39%
2007-2010	-2.94%	-1.29%	-2.28%	-1.52%	-1.20%	-1.49%	-1.16%	-0.67%	-0.39%	-0.82%	-0.54%	-0.12%
Average returns of 1%-Δ$CoVaR sorted portfolios												
1987-2013	0.30%	0.61%	1.01%	0.73%	0.82%	0.98%	1.11%	1.11%	1.11%	0.94%	0.79%	0.95%
2007-2010	-2.97%	-1.34%	-1.15%	-1.27%	-1.77%	-1.67%	-1.93%	-1.07%	-0.92%	-0.71%	-0.88%	-0.69%
Average returns of 1%-MES sorted portfolios												
1987-2013	0.90%	0.89%	0.74%	0.88%	0.65%	0.83%	1.26%	0.65%	1.00%	1.39%	1.25%	1.47%
2007-2010	-1.29%	-1.00%	-0.99%	-1.82%	-1.52%	-1.21%	-0.56%	-1.79%	-0.69%	-0.28%	0.22%	-1.11%

Table 2 Average returns of portfolios. The table presents average returns of 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES sorted portfolios. The first portfolio displays the average return of firms that were sorted into the lowest decile of 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES levels, and the 10^{th} portfolio displays the average return of firms that were sorted into having the highest values of 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES in the sample. Sorts are executed each month, firms may therefore jump in between portfolios at different periods in time.

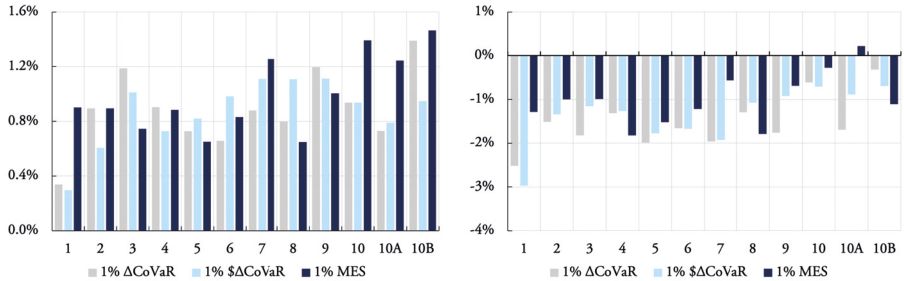

Figure 1 Average returns of portfolios. The left figure displays a bar chart of average returns of portfolios 1-10A,B sorted according to levels of 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES during the sample period 1987-2013. The right figure presents values during the crisis years 2007-2010.

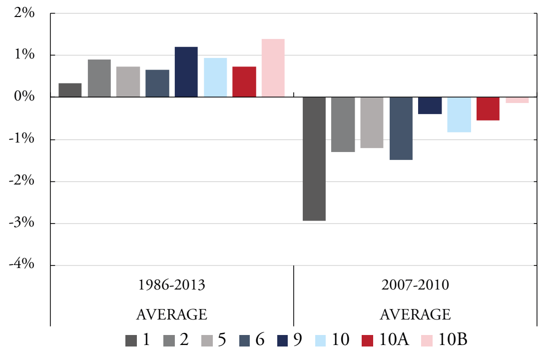

Figure 2 Average returns of portfolios. The figure displays a bar chart of average returns for 1%-ΔCoVaR sorted portfolios during the sample period 1987-2013 (left pane) and during the crisis 2007-2010 (right pane). For clarity reasons, only portfolios 1,2,5,6,9,10, 10AB are illustrated in figures 2-4.

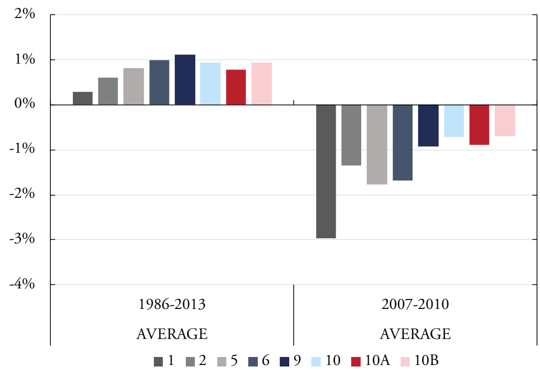

Figure 3 Average returns of portfolios. The figure displays a bar chart of average returns for 1%-Δ$CoVaR sorted portfolios during the sample period 1987-2013 (left pane) and during the crisis 2007-2010 (right pane).

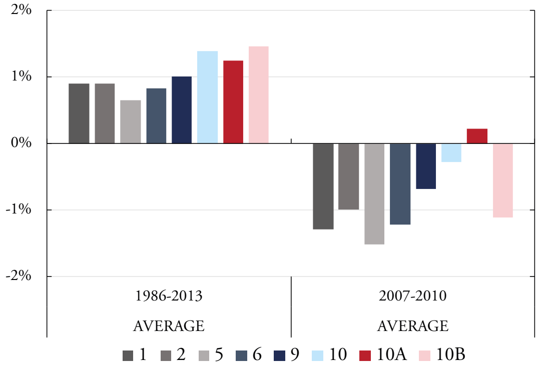

Figure 4 Average returns of portfolios. The figure displays a bar chart of average returns for 1%-MES sorted portfolios during the sample period 1987-2013 (left pane) and during the crisis 2007-2010 (right pane).

Another way to examine the different portfolios is to observe how these hypothetical portfolios would perform over time should one have formed investment strategies based on systemic importance at the beginning of the sample period and updated the portfolios mid-monthly (Figures 5-7). We therefore turn to graphically observing the cumulative returns of these portfolios that are based on investing (taking long positions) in stocks with different levels of systemic risk. For clarity reasons, only the cumulative returns of portfolios 1, 2, 5, 6, 9, 10, 10A and 10B are plotted.

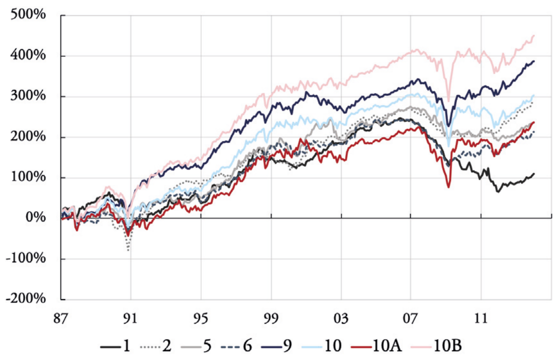

Figure 5 Cumulative returns of portfolios. The figure plots the cumulative returns of 1%-ΔCoVaR sorted portfolios during 1987-2013. Some portfolios are left out due to visibility reasons. The top line is the 10B portfolio, and the bottom line is the 1st portfolio, at the end of the time series.

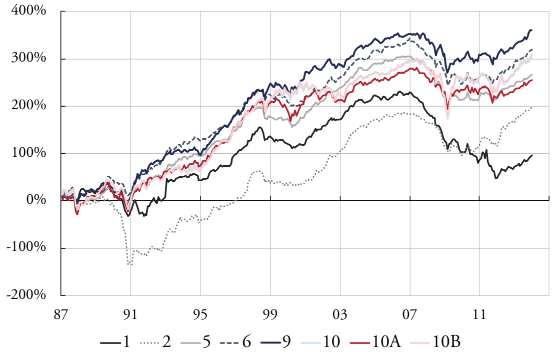

Figure 6 Cumulative returns of portfolios. The figure plots the cumulative returns of 1%-Δ$CoVaR sorted portfolios during 1987-2013. Some portfolios are left out due to visibility reasons. The top line is the 9th portfolio, and the bottom line is the 1st portfolio, at the end of the time series.

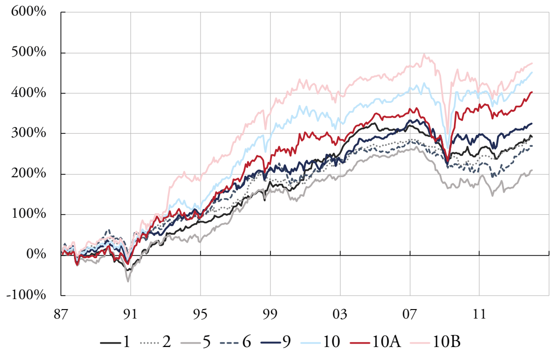

Figure 7 Cumulative returns of portfolios. The figure plots the cumulative returns of 1%-MES sorted portfolios during 1987-2013. Some portfolios are left out due to visibility reasons. The top line is the 10B portfolio, the bottom line is the 5th portfolio, at the end of the time series.

We start by noticing that investing based on different systemic risk levels yields different results. We may also identify a set of crisis periods based on how these portfolios performed. The financial crisis of 2008-2009 is seen most clearly in the graphs, with a sharp drop around the years 2008-2009. Due to the fact that the sample period starts in January 1987 it is hard to spot the 1987 crash, although the housing and banking crisis of the early 1990s is clearly visible.

If we turn to specific portfolios, we can see that, for example, portfolio 10B, that is the portfolio with the most systemic financial institutions in the sample, outperforms the rest of the portfolios during almost the whole time period and especially so during the financial crisis. This is true for the 1%-$\Delta CoVaR$ and 1%-

MES sorted portfolios. The worst performing portfolio is the 1st, according to *ΔCoVaR* specifications. At first glance, these findings seem to be in conjecture with the fact that investors are compensated for higher risk through higher returns, even though this is not visible (nor statistically inferred) in average returns, i.e. that systemically important firms are riskier.

Another interesting take on the portfolios is to what extent the same bank stays in the same systemic risk sorted portfolio, i.e. how persistent the different systemic risk measures are in terms of sorting banks into different portfolios over time. A more persistent systemic risk measure is preferred, especially concerning highly systemic institutions versus less systemic institutions, since being systemically important is typically seen as rather static over time. For example, the list of globally systemic financial institutions that the FSB constructs every year has not changed significantly since they first published the list in 2012. Another common problem when dealing with systemic risk measures in general is furthermore that they often do not give a consistent ranking of systemically important institutions. The ranking is consistent over time within each measure, but often not in between measures. The issue is studied empirically and theoretically in e.g. Benoit et al. (2013) and Acharya et al. (2012).

To get an idea about persistence I estimate transition probabilities between and within different portfolios from one month to another. I estimate the probability of a bank staying in the same portfolio in time $t+1$ as in time t, as well as the probability of moving to another portfolio. The probabilities for firms sorted according to 1%-*ΔCoVaR* (my main measure of systemic risk contributions) are found in Table 3.

Portfolio 1		2	3	4	5	6	7	8	9	10
1	**0.95**	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.04	**0.80**	0.14	0.01	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.14	**0.63**	0.20	0.03	0.00	0.00	0.00	0.00	0.00
4	0.00	0.01	0.19	**0.53**	0.22	0.04	0.01	0.00	0.00	0.00
5	0.00	0.00	0.03	0.21	**0.50**	0.21	0.04	0.01	0.00	0.00
6	0.00	0.00	0.01	0.04	0.21	**0.49**	0.22	0.04	0.01	0.00
7	0.00	0.00	0.00	0.01	0.04	0.22	**0.47**	0.22	0.04	0.00
8	0.00	0.00	0.00	0.00	0.01	0.03	0.21	**0.50**	0.21	0.03
9	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.21	**0.56**	0.18
10	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.18	**0.79**

Table 3 Transition probability matrix. The table presents monthly switching probabilities. The columns correspond to the portfolio that a bank is currently placed in, and the rows represent the portofolio the bank is switching to. For example, the probability of staying in portfolio 1 (being sorted into the first decile based on a bank's level of systemic risk) between time t and t+1 is 95 %, and the probability of moving to the 4th portfolio in time t+1 (4th decile) if you are currently sorted into portfolio 3 is 19%, on average. Rows/columns should obviosuly add up to 1.00 but may not do so in the table due to rounding errors.

The switching probabilities of banks sorted into portfolios 1 and 10 are high relative to the rest of the probabilities. The probability of staying in the lowest decile from one month to another is as high as 95% and the probability of staying in the 10th portfolio is 79%. The probabilities are highest for conjoining portfolios and drop to zero afterwards, indicating that it is rather unlikely to go from being highly systemic to less systemic, and the other way around.

6.2 Regressions – explaining returns with risk factors

I now regress excess returns for each systemic risk sorted portfolio according to equation 10, which is stated again below. A total of 15 regressions are executed each for 1%-*ΔCoVaR*, 1%-*Δ$CoVaR* and 1%-MES sorted portfolios; portfolios 1 to 10, and portfolios 10A, 10B as well as investment strategies 10-1, 10A-1 and 10B-1 following the setup of GL (2015). For robustness purposes (see section 6.3), 5% conditioning thresholds are also considered for the sorted portfolios. Regressions with portfolios sorted according to market capitalization and book value are also executed (but not presented) in order to replicate the results of GL (2015). A more detailed description of the performed regressions follows next, where the following cross-sectional model is estimated

$$R_t^p - R_t^f = \alpha^p + \boldsymbol{\beta}^{\boldsymbol{p}\prime} \boldsymbol{f_t} + \varepsilon_t^p \tag{10}$$
$$\boldsymbol{f_t} = [mkt\ smb\ hml\ ltg\ crd]$$

To recapitulate, monthly value-weighted and systemic risk sorted bank stock portfolio returns (R_t^p), in excess of the risk-free rate (R_t^f), are regressed on the three Fama-French (1992a) stock factors (*market*, *small-minus-big* and *high-minus low*) and two bond factors (U.S. 10-yr government bond total return index (*ltg*) and excess returns on investment grade corporate bonds index (*crd*)). R_t^i represents the monthly return on the i^{th} *ΔCoVaR*, *Δ$CoVaR* or MES sorted portfolio.

As previously argued, I expect the risk-adjusted returns of highly systemic firms to be lower than for less systemic firms. I expect this due to the loss absorbing capacity of the government that will be more inclined to save a systemic firm than a firm that is not considered systemic (or is at least relatively less systemic), following the reasoning and results of GL (2015). This is typically the case for banks – banks that are important for financial stability are not "allowed" to simply go into bankruptcy, because their failure would have severe consequences for the real economy and disrupt financial stability. The conjecture, as stated in Acharya et al. (2013), is that implicit support will affect the stock price of a bank by reducing its cost of funds and thereby making it more profitable.

In order to analyze this statement, I focus on the intercepts, the *alphas*, in the estimated regressions, as well as observing how the other risk factors enter in order to control for the "standard" reasons for why returns may differ in the cross-section of systemically important banks' stock returns. The alphas should optimally be negative (positive) and statistically significant, for the most systemic portfolios, to accept (reject) the suggested statement in GL (2015). If alphas are negative and significant it means that i) the included common risk factors are not enough to explain the return structure of these portfolios and ii) these portfolios indeed have lower excess returns than portfolios that are not as systemic. Drawing the line between what is systemic and what is not is of course difficult and subjective, but I decide to draw this line at portfolio number 9 based on the summary statistics in Table 1. This conclusion is also based on cross-checking with the list provided by the FSB and general information about domestic systemically important banks (D-SIBs) obtained from national authorities.

Therefore, I am mostly interested in finding negative and statistically significant alphas in the 9th portfolio and further, including the spread portfolios (investment strategies).

To follow the set-up of GL (2015) I also evaluate the statement by considering the expected return of an investment strategy that includes taking a long position in stocks of highly systemic firms and a short position in stocks of non-systemic firms, *spreads*. Forming this type of portfolio is based on the same idea as for example the "big minus small" Fama-French portfolio/factor. We have some stocks that are "winners" and some that are "losers" depending on a certain characteristic and this can be exploited. In this case, the forming of a long-short investment strategy based on systemic importance indicates that highly systemic firms will underperform non-systemic firms in the long run, in which case, if this is perceived as true among investors, the alphas should be negative and significant (or naturally the other way around if this is not the case). Even though excess returns may not be significant in isolation, the difference may well be significant, hence the formation of such portfolios. Results are presented in Table 4 with the different systemic risk measures labelled as Panel A, B and C.

Panel A	Regression results based on 1%-ΔCoVaR sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10-1	10A	10B	10A-1	10B-1
Mkt	0.697***	0.7127***	0.8596***	0.8509***	0.9652***	0.9378***	1.0907***	1.1548***	1.254***	1.4927***	0.7957***	1.4985***	1.5241***	0.8013***	0.8271***
Smb	0.4914***	0.2606***	0.3954***	0.1646*	0.0854	-0.0340	-0.1672**	0.0082	-0.0722	0.1244	-0.6158***	-0.1344	-0.0867	0.6257***	-0.5783***
Hml	0.5326***	0.4415***	0.7096***	0.6758***	0.6197***	0.4567***	0.6526***	0.7955***	0.7900***	0.8296***	0.2970**	0.7985***	0.9051***	0.2658*	0.3726***
Ltg	0.4614***	0.2266	0.4255**	0.2032	0.0355	0.1665	0.0875	0.1479	0.2404	0.0326	-0.4286**	-0.1739	0.0656	-0.6352**	-0.3957*
Crd	-0.4099*	0.0382	-0.1796	-0.0495	-0.0428	-0.1937	0.0385	-0.1429	-0.1067	-0.2582	0.15158	-0.0236	0.3230	0.3862	0.0868
Alfa	-0.0060**	-0.0008	0.0005	-0.0017	-0.0034	-0.0032	-0.0029	-0.0041	-0.0012	-0.0040	0.0019	-0.0061*	0.0002	-0.0001	0.0061
R^2	0.3061	0.3318	0.4052	0.4172	0.4675	0.4200	0.5960	0.5908	0.6485	0.6864	0.2725	0.5920	0.5929	0.2181	0.2486

Panel B	Regression results based on 1%-Δ$CoVaR sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10-1	10A	10B	10A-1	10B-1
Mkt	0.6024***	0.5274***	0.5193***	0.5559***	0.6525***	0.6975***	0.8770***	0.9572***	1.077***	1.4667***	0.8641***	1.1430***	1.4994***	0.5405***	0.8969***
Smb	0.4183***	0.5338***	0.3654***	0.3849***	0.3255***	0.3928***	0.4053***	0.4537***	0.0981	-0.1620**	-0.5803***	-0.1393**	-0.1757**	-0.5577***	-0.5941***
Hml	0.6093***	0.4407***	0.4731***	0.5624***	0.5261***	0.6067***	0.6385***	0.7757***	0.7664***	0.7903***	0.1810	0.7608***	0.7806***	0.1515	0.1713
Ltg	0.3994**	-0.0471	0.0991	-0.0025	0.0290	0.1064	0.0473	0.4683***	0.3732***	0.0517	-0.3477*	0.2934**	0.0101	-0.1059	-0.3893*
Crd	-0.3323	0.1267	0.0418	0.0578	0.0090	0.0373	-0.0912	-0.2830*	-0.2115	-0.2957*	0.0365	-0.2033	-0.2821	0.1290	0.0502
Alfa	-0.0059**	-0.0023	0.0017	-0.0012	-0.0008	0.00006	0.0007	0.0009	-0.0011	-0.0035	0.0023	-0.0041**	-0.0035	0.0018	0.0023
R^2	0.2694	0.2575	0.3582	0.4306	0.5171	0.5553	0.6292	0.6446	0.6419	0.7223	0.3031	0.6583	0.7008	0.1756	0.03059

Panel C	Regression results based on 1%-MES sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10–1	10A	10B	10A-1	10B-1
Mkt	0.4836***	0.5687***	0.5538***	0.6718***	0.7034***	0.8155***	0.9853***	1.0153***	1.2083***	1.3201***	-1.0351***	1.3263***	1.5895***	-1.0208***	1.1057***
Smb	0.2369**	0.2235**	0.1947**	0.1627**	0.2425***	0.1151	-0.0743	-0.0358	-0.1188	-0.1383	0.2592**	0.0169	-0.0645	0.2880**	0.3014**
Hml	-0.5093***	0.4291***	0.3992***	0.4868***	0.3821***	0.4180***	0.5034***	0.5948***	0.7225***	0.8050***	-0.2759**	0.7416***	0.6752***	-0.2460*	-0.1658
Ltg	-0.1337	0.0930	0.0564	0.1745	0.1161	0.2213	-0.0282	0.0990	0.1628	0.1872	0.0801	-0.0661	-0.0236	0.1166	-0.1100
Crd	0.2514	0.0607	0.1331	-0.2160	0.0486	-0.1635	0.0512	-0.0254	-0.3865*	0.0169	0.2801	0.0009	-0.1469	0.2077	0.3984
Alfa	0.0026	-0.0006	0.0005	0.0016	-0.00291	0.00004	-0.0027	-0.00272	0.0002	-0.0061**	0.0008	-0.0043	-0.0003	-0.0003	0.0029
R^2	0.1885	0.2281	0.2612	0.4017	0.4237	0.3983	0.4657	0.4761	0.5661	0.5942	0.2804	0.5803	0.6196	0.2522	0.2909

Table 4 Regression results. The table presents estimates from regressions of monthly value-weighted excess returns of each systemic risk sorted portfolio on the three Fama-French factors (*market, smb* and *hml*) and two bond factors (*ltg* and *crd*) (equation 10), described in section 5.2. Systemic importance is defined by estimating 1%-ΔCoVaR, 1%-Δ$CoVaR and 1%-MES. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. As opposed to Table 1 in GL (2015), alphas are not annualized nor presented in percentages. Standard errors are adjusted for heteroskedasticity and autocorrelation. The sample period is from 1987 to 2013.

Panel A in Table 4 depicts the regression results of equation 10, where the excess return portfolios are formed by sorting each bank based on its level of 1%-*ΔCoVaR*, each month. The portfolios are ranked from smallest (small, the first decile) to largest (large, the tenth decile).

Summarizing first some portfolio characteristics, we observe in Table 1 that the first portfolio has a negative average 1%-*ΔCoVaR* of -0.28%. The average value monotonically increases to 4.98% in the 10^{th} portfolio. If we look at the regression results in Table 4, we see that the market *(mkt)* and value (*hml)* factors have significant factor loadings through all portfolios. Looking at the market factor, we observe that the factor loading is increasing in size with portfolios that contain firms with a higher level of systemic risk. For example, a portfolio that contains firms with the lowest level of systemic risk in the sample has an average beta of 0.6 as compared to portfolio number 10, which includes firms that are the most systemic according to the measures, has an average beta of 1.47. This tells us that the most systemic banks in our sample were approximately 2.45 times more exposed to market risk than the least systemic firms in the sample. In the same manner, the loading on the *hml* factor is positive and significant for all of the portfolios, through all of the systemic risk specifications. The *hml* loading does not show a clear systematically increasing or decreasing pattern, but more systemic stocks tend to have a higher loading. The loading of the size factor instead decreases as we move to the right in the table, increasing systemic risk in portfolios. This is also consistent with theory as small stocks tend to have a higher sensitivity to the size factor as these firms typically have a more volatile business environment which translates into higher costs of capital compared with larger firms. Particularly, firms that are very large, also tend to be systemic, hence a statistically significant and negative loading on the size factor would also contribute to the statement that highly systemic firms earn lower returns. As argued in GL (2015), the pattern of a decreasing size factor loading is consistent with the fact that the government helps to safeguard large commercial banks. The size factor loading is found significant at the 1% level for the lower half of the portfolios, as well as for the 10-1, 10A-1 and 10B-1, and insignificant and even negative for the upper (right in table) half of the portfolios.

If we consider the bond factors, we see no statistically significant factor loadings except for the first portfolio. Flannery and James (1984) interpret the bond factor loading *ltg* as a measure of interest rate sensitivity stemming from maturity mismatch in assets and liabilities. This can also be interpreted as a factor for business cycle risk, to which less systemic firms seem to be more exposed to. Believing that systemic importance is closely related to size, the loading on this factor is expected to be higher for less systemic (smaller) firms. In my results, this factor is almost never significant, but has a positive sign and is overall decreasing as we move to the right in the table. The first portfolio exhibits a bond factor loading of 0.46 which is statistically significant on the 1% level. This is also the case for the third portfolio and for the 10A-1 and 10B-1 portfolios. For the other bond factor, the *crd*, which is supposed to measure exposure to credit risk, no significance is found in the estimations, and the signs and magnitudes of the coefficients are rather jumpy. The factor loadings on both these factors are, albeit insignificant, larger for less systemic firms. Since there is a high correlation between systemic importance and size, higher loadings on these factors may point to the fact that smaller banks are less sophisticated in their usage of credit and interest rate hedges compared to bigger banks. This view is also established in e.g. Minton et al. (2009) and Schuermann and Stiroh (2006). Consequently, this motivates smaller and insignificant loadings for more systemic banks.

The main interest, however, lies in the intercept, the *alpha*, or the excess return that cannot be explained by the included common risk factors. I observe non-zero, but insignificant, alphas in almost all of the portfolio regressions. The estimated intercepts decrease, non-monotonically, when we go from the first portfolio (-0.6%) to the tenth portfolio (-0.4%). The largest intercept is found for portfolio 10A (-0.6%). The majority of the alphas are insignificant; however, for the first and 10A portfolios the alpha is significant at the 10% level. Finally, looking the R^2 values, we see that they, interestingly, increase as we move from the first to the tenth portfolio indicating that the included factors explain excess returns better for stocks that are relatively more systemic. Concludingly, standard risk factors seem to succeed in explaining systemic importance, and any potential spreads, as revealed by both high R^2 and insignificant alphas.

Panel B instead depicts the regression results of equation 10, where the left hand side represents the returns of portfolios that are formed based on each bank's *Δ$CoVaR*, that is, the estimated *ΔCoVaR* for each firm *i,* multiplied by the book value of the firm *i*. In this way, we relate systemic risk to *size* more directly in dollar terms (in million USD) expressed as the expected value of assets lost for firm i when the market is in distress. In principle, it is another perspective on systemic importance as firms that incur larger losses have a larger impact on financial markets and therefore also a higher probability of affecting overall financial stability. The results are very similar to the results for the *ΔCoVaR* regressions. Alphas are also insignificant. Similarly, to the results for *ΔCoVaR* sorted portfolios, the 1st portfolio and the 10A portfolio have negative and significant alphas at the 5% level. Overall, the three Fama-French factors are mostly significant, whereas for most of the portfolios the two bond factors are statistically insignificant. As in Panel A, R^2's are increasing as we move to more systemic portfolios.

Similarly, the regression results when we instead sort firms based on their level of 1% *marginal expected shortfall* (Panel C) look very similar to those of the 1%-*ΔCoVaR* specification. These two measures are similar in terms of their construction and a MES regression specification can, in principle, be seen as part of a sensitivity analysis rather than adding more value to the main results.

There are a few explanations at work that could illuminate the insignificance inherent in my results. The first that comes to mind is that systemic risk as measured by *ΔCoVaR* and MES, and hence the aspect of *too-big-to-fail,* could be already accounted for, partially or fully, in the included risk factors, especially the size and market factors. First, systemic risk is, although not perfectly, highly correlated with size and the general understanding is that the bigger you are, the more important you are for the financial system. However, risk premia in markets are determined by investors and their behaviour and expectations while they trade. Hence, if investors require a relatively lower risk premium for *too-big-to-fail* institutions, then we simply will get a lower, or none, risk premium for these institutions. However, which institutions are *too-big-to-fail* is perhaps unobservable for investors, or observed with uncertainty. For example, many investors thought that Lehman Brothers was *too-big-to-fail* in 2008, even though there was no bail out. My results might therefore be driven by which institutions that investors perceive to be *too-big-to-fail* rather than which institutions are, or should be in theory, *too-big-to-fail*. Potentially, the market may use size as a proxy of *too-big-to-fail*, and rightfully so, since it is more easily observed than measures such as ΔCoVaR or MES that require some calculations.

Connected to the reasoning above, another interpretation at work could be that GL (2015) capture a "true" (negative) risk premium for the institutions that investors perceive to be *too-big-to-fail*, whereas I in my paper identify those institutions who in theory may be more likely to be *too-big-to-fail*, but not perceived as such by the market. This leads to a very interesting possibility that due to uncertainty about which institutions are *too-big-to-fail*, the market may "incorrectly reward", or "assign" institutions with a negative risk premium. This then implies a potential overall mispricing of *too-big-to-fail* institutions. Subsequently, some institutions that may be more likely to be *too-big-to-fail* (as by systemic risk measures) are not punished with a lower risk premium, even though they should in theory, due to the fact that the market fails to correctly identify the most likely *too-big-to-fail* institutions. Perceptions of risk are extremely hard to quantify, especially during times of financial distress. Their effect, however, has important implications for the economy.

6.3 Sensitivity analysis

As a brief sensitivity exercise, the same analysis is completed for a less extreme position in the left tail of the return distribution, the fifth quantile. Hence, for all firms in my sample I re-estimate the measures *ΔCoVaR*, *Δ$CoVaR* and MES using the fifth quantile as the conditioning event.

$$\Delta CoVaR_{t,5\%}^{j|\mathbb{C}(X^i)} = \hat{\beta}_{5\%}^{j}\left(VaR_t^{i,5\%} - VaR_t^{i,50\%}\right) \tag{11}$$

$$\Delta \$CoVaR_{t,5\%}^{j|\mathbb{C}(X^i)} = {}^{\$}Size^i \cdot \Delta CoVaR_{t,5\%}^{j|\mathbb{C}(X^i)} \tag{12}$$

$$MES_t^{i|j} = -E_{t-1}\left[r_t^i \middle| r_t^j \leq -VaR_t^{j,5\%}\right] \tag{13}$$

Summary statistics of portfolios sorted according to the new conditioning events can be found in Tables 6 and 7 in the Appendix. The results mainly follow those of the 1%-specifications; however, they are naturally somewhat weaker due to the less extreme position in the distribution of returns. Estimating equation 10 also confirms the results presented in Table 4 and do not lead me to draw any other conclusions than those in the previous section. The regression results for the above three systemic risk specifications can be found in Table 5 in the Appendix.

7 Conclusion

To study the implicit government guarantee implications on equity returns, this paper analyzes returns of portfolios containing banks that are different in terms of their systemic importance. The most fundamental result in finance tells us that higher risk also means a greater probability of a higher return. However, risky financial firms also pose a threat to the financial system and therefore, if these firms are considered *too-big-to-fail*, the government will be inclined to intervene in order to safeguard financial stability. From this perspective it is argued in, i.a. Gandhi and Lustig (2015), that the risk adjusted expected return should be lower for highly risky and systemic banks than for less systemic banks, due to the loss-absorbing capacity of the systemic banks' tail risk by the government. Systemic importance is determined by estimating three systemic risk measures for each firm, monthly, from 1987-2013, which is the sample period covered in this paper. I use Adrian and Brunnermeier's (2016) *ΔCoVaR*, *Δ$CoVaR* and the marginal expected shortfall, MES, as defined in Brownlees and Engle (2010) and Acharya et al. (2010) to distinguish systemically important firms as these measures should be able to say something about the bail-out probability given by the government. Sorted firms, grouped into portfolios, are then analyzed in a Fama-French framework, where the intercept, or *alpha*, is focused on. Within this framework, I find no evidence that points towards the perception that implicit government guarantees inferred lower risk-adjusted returns during the period 1987-2013. There are several potential explanations at work here. First, what happens in the market is more or less decided by the market. If investors fail to recognize *too-big-to-fail* institutions, or identify them in a different way that is not inherent in systemic risk measures, risk premia will not show. Second, a "*too-big-to-fail*"-premium, as the name implies, may well be already incorporated in and accounted for specifically by the size and market factors.

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Panel A	Regression results based on 5%-ΔCoVaR sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10-1	10A	10B	10A-1	10B-1
Mkt	0.6973***	0.6868***	0.8550***	0.8588***	0.9675***	0.9329**	1.0911***	1.1550***	1.2640***	1.4890***	0.7916***	1.4878***	1.5169***	0.7905***	0.8195***
Smb	0.4887***	0.2251***	0.4109***	0.1588*	0.0788	-0.0318	-0.1629**	-0.0019	-0.0793	-0.1184	-0.6071***	-0.1336	-0.0724	-0.6223***	-0.5612***
Hml	0.5334***	0.4596***	0.7088***	0.6714***	0.6232***	0.4511***	0.6523***	0.7771***	0.7934***	0.8349***	0.3014**	0.8097***	0.9200***	0.2762*	0.3865***
Ltg	0.4706***	0.1778	0.4160**	0.2211	0.0274	0.1730	0.0871	0.1552	0.2728**	0.0173	-0.4532**	-0.1997	0.0422	-0.6703***	-0.4284*
Crd	-0.4235*	0.0397	-0.1482	-0.0796	-0.0383	-0.1940	0.0316	-0.1403	-0.1281	-0.2491	0.1744	0.0019	-0.3234	0.4254	0.1002
Alfa	-0.0059**	-0.0005	0.0005	-0.0017	-0.0031	-0.0033	-0.0028	-0.0041*	-0.0011	-0.0039	0.00197	-0.0064**	0.0003	-0.0005	0.0062
R^2	0.3044	0.3522	0.3974	-0.4111	0.4703	0.4167	0.5957	0.5948	0.6519	0.6844	0.2708	0.5915	0.5847	0.2177	0.2414

Panel B	Regression results based on 5%-Δ$CoVaR sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10-1	10A	10B	10A-1	10B-1
Mkt	0.6024***	0.5291***	0.5239***	0.5529***	0.6493***	0.6997***	0.8758***	0.9541***	1.0789***	1.4658***	0.8633***	1.1379***	1.5003***	0.5354***	0.8979***
Smb	0.4189***	0.5341***	0.3676***	0.3801***	0.3384***	0.3836***	0.4066***	0.4368***	0.0984	-0.1601**	-0.5791***	-0.1329**	-0.1759**	-0.5519***	-0.5949***
Hml	0.6091***	0.4384***	0.4791***	0.5595***	0.5355***	0.5986***	0.6389***	0.7796***	0.7595***	0.7924***	0.1833	0.7698***	0.7802***	0.1607	0.1711
Ltg	0.3994**	-0.0449	0.1044	-0.0146	0.0324	0.1055	0.0499	0.4622***	0.3858***	0.0472	-0.3522*	0.2793**	0.0096	-0.1200	-0.3897*
Crd	-0.3331	0.1269	0.0427	0.0526	0.0449	0.0101	-0.0943	-0.2804*	-0.2195	-0.2926	0.0405	-0.1749	-0.2890	0.1582	0.0441
Alfa	-0.0059**	-0.0023	0.0017	-0.0012	-0.0008	0.00006	0.0007	-0.0010	-0.0011	-0.0036	0.0023	-0.0042**	-0.0034	0.0017	0.0024
R^2	0.2695	0.2582	0.3568	0.4310	0.5256	0.5506	0.6288	0.6472	0.6336	0.7225	0.3028	0.6598	0.7011	0.1742	0.3063

Panel C	Regression results based on 5%-MES sorted portfolio excess returns													
	1	2	3	4	5	6	7	8	9	10	10–1	10A	10B	10A-1	10B-1
Mkt	0.5773***	0.5339***	0.6195***	0.6793***	0.8620***	0.9637***	1.1933***	1.2675***	1.4046***	1.5330***	0.9556***	1.3133***	1.6776***	0.7366***	1.1002***
Smb	0.2460***	0.3373***	0.1961***	0.3212***	0.0309	-0.0251	0.0186	-0.0326	-0.1657*	-0.0900	-0.3360***	0.1612	-0.1422	-0.0847	-0.3882***
Hml	0.4511**	0.3445***	0.3148***	0.5213***	0.3434***	0.5556***	07346***	0.8562***	0.08008***	0.7259***	0.2748**	0.8787***	0.8418***	0.4276***	0.3907***
Ltg	0.0801	0.1371	0.0678	0.1723	0.1990	0.0816	0.0331	0.2810*	-0.0878	0.0640	-0.0161	0.2683	-0.0426	0.1882	-0.1227
Crd	-0.0340	-0.1173	0.0990	0.0895	-0.03044	-0.1674	0.0198	-0.4881**	0.1106	-0.2142	-0.1801	0.0138	-0.0464	0.0479	-0.0124
Alfa	-0.0027	0.0023	0.0005	-0.00006	-0.0017	-0.0026	-0.0052	-0.0013	-0.0039	0.0018	0.0045	-0.0023	-0.0025	0.0003	0.0002
R^2	0.3203	0.3298	0.3614	0.4030	0.3977	0.4902	0.5584	0.5831	0.6255	0.6211	0.2679	0.5135	0.5988	0.1651	0.3011

Table 5 Regression results. The table presents estimates from regressions of monthly value-weighted excess returns of each systemic risk sorted portfolio on the three Fama-French factors (*mkt, smb* and *hml*) and two bond factors (*ltg* and *crd*) (equation 10), described in section 5.2. Systemic importance is defined by estimating 5%-ΔCoVaR, 5%-Δ$CoVaR and 5%-MES. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. As opposed to table 1 in GL (2015), alphas are not annualized nor presented in percentages. Standard errors are adjusted for heteroskedasticity and autocorrelation. The sample period is from 1987 to 2013.

Portfolio	1	2	3	4	5	6	7	8	9	10	10A	10B
Average returns of 5%-ΔCoVaR sorted portfolios												
1987-2013	0.13%	1.08%	0.99%	0.93%	0.69%	1.01%	0.87%	0.81%	0.54%	1.07%	0.89%	1.19%
2007-2010	-2.52%	-1.51%	-1.82%	-1.31%	-1.98%	-1.66%	-1.96%	-1.29%	-1.76%	-0.61%	-1.69%	-0.32%
Average returns of 5%-Δ$CoVaR sorted portfolios												
1987-2013	0.34%	0.47%	0.80%	0.79%	0.72%	1.24%	0.77%	1.19%	1.08%	0.96%	0.90%	0.94%
2007-2010	-2.10%	-1.39%	-1.74%	-1.39%	-1.86%	-2.08%	-1.79%	-0.90%	-1.23%	-0.70%	-0.65%	-0.70%
Average returns of 5%-MES sorted portfolios												
1987-2013	0.54%	1.00%	0.90%	0.98%	0.81%	0.73%	0.72%	1.08%	0.97%	1.55%	1.21%	1.25%
2007-2010	-1.46%	-1.08%	-0.84%	-0.80%	-1.35%	-2.10%	-1.87%	-0.30%	-0.56%	-0.28%	-0,11%	-0.71%

Table 6 Average returns of portfolios. The table presents average returns of 5%-ΔCoVaR, 5%-Δ$CoVaR and 5%-MES sorted portfolios. The first portfolio displays the average return of firms that were sorted into the lowest decile of 5%-ΔCoVaR, 5%-Δ$CoVaR and 5%-MES levels, and the 10th portfolio displays the average return of firms that were sorted into having the highest values of 5%-ΔCoVaR, 5%-Δ$CoVaR and 5%-MES in the sample. Sorts are executed each month, firms may therefore jump in between portfolios at different periods in time.

Portfolio	1	2	3	4	5	6	7	8	9	10	10A	10B
Average 5%-ΔCoVaR												
1987-2013	0.08%	0.41%	0.61%	0.79%	1.02%	1.26%	1.53%	1.87%	2.28%	2.98%	2.73%	3.22%
2007-2010	-0.10%	0.30%	0.54%	0.74%	0.99%	1.27%	1.63%	2.11%	2.73%	3.76%	3.34%	4.16%
Average 5%-Δ$CoVaR (in million USD)												
1987-2013	0.05	0.23	0.48	0.81	1.32	3.14	5.86	13.67	44.55	997.80	152.77	1,806.93
2007-2010	0.00	0.09	0.22	0.40	0.68	1.18	2.67	6.55	20.60	1,454.1	175.31	2,782.60
Average 5%-MES												
1987-2013	-0.46%	0.01%	0.20%	0.39%	0.58%	0.80%	1.08%	1.41%	1.88%	2.88%	2.40%	3.34%
2007-2010	-0.50%	0.01%	0.23%	0.44%	0.67%	0.99%	1.47%	1.99%	3.25%	3.80%	3.29%	4.30%

Table 7 Average systemic risk in portfolios. The table presents average values of the sorting variable, 5%-ΔCoVaR, 5%-Δ$CoVaR and 5%-MES, for different portfolios. The first portfolio consists of firms that have the lowest level of the mentioned measures, and the 10th portfolio consists of firms that have the highest level of the mentioned measures. Note that the values are inverted; CoVaR and MES are losses. A negative value in the above table (such as for example in portfolio 1) hence represents a gain, i.e. a positive contribution/return. Sorts are executed each month, firms may therefore jump in between portfolios at different periods in time.

Equity volatility and leverage – loan level evidence

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Abstract

This paper is the first to use loan level data to investigate the relationship between equity volatility and financial leverage on the firm level. We use a comprehensive dataset of large syndicated loans with a total loan amount in excess of 12 trillion USD. This allows us to identify precisely when a company experiences a large change in leverage. In contrast to several previous studies that have relied only on accounting data, we find very clear results that increased financial leverage increases equity volatility. Our findings are robust to controlling for time trends in variance as well as for the type and purpose of the loan.

Key words: volatility, leverage, syndicated loans, event study, Merton
JEL codes: G10, G14, G21, G32

1 Introduction

There is a large dispersion in equity volatility across firms. While the time series behaviour of equity volatility has been extensively studied starting with the seminal paper of Engle (1982), we still know surprisingly little about the determinants of firm specific equity volatility. Even if a large part of firm specific volatility can be diversified away, the total volatility of a firm (systematic and idiosyncratic) is still very important for all investors who are imperfectly diversified (Campbell et al. (2001)). Further, idiosyncratic volatility is priced as shown in Ang et al. (2006) and Herskovic et al. (2016) and it is an important component of trading frictions (Shleifer and Vishny (1997)). Additionally, the total volatility of a stock is the key input to pricing derivatives. In the words of Goyal and Santa-Clara (2003), *idiosyncratic risk matters*! Understanding the firm level determinants of stock market volatility is not only important for the reasons stated above, but it also constitutes a first step in understanding the variation in aggregate stock market volatility over time discussed in e.g. Campbell et al. (2001), Brandt et al. (2010) and Bekaert (2019). This paper contributes to our understanding of firm level determinants of volatility by studying the relationship between firm indebtedness (leverage) and equity market volatility using a dataset on loan level data covering a total loan amount of roughly USD12tn.

Measuring the relationship between volatility and leverage is challenging for several reasons. Firms choose their leverage strategically and firms that are safe in a business sense (have low asset volatility) will generally pick high financial leverage, therefore obfuscating the true relationship between stock market volatility and leverage, see e.g. Choi and Richardson (2016). This self-selection problem makes it almost impossible to correctly measure the relationship between leverage and volatility in the cross-section of firms. The alternative, to study changes over time for a given firm, by e.g. running panel regressions with firm fixed effects, results in low statistical power since, typically, a given firm's leverage does not change much over time compared to the cross-sectional variation. A further difficulty is that changes in leverage can usually only be observed from accounting data and thus only measured at a quarterly or annual frequency.

We propose to solve these problems by using a large dataset on detailed loan level information. This allows us to identify on what day exactly a firm is given a new loan as well as the size of the loan. Thus, we can calculate the change in volatility for a given firm shortly before and after it has experienced a large increase in leverage. Identification hence comes from (a large) within firm change during a short period of time. This substantially mitigates the problem of unobserved heterogeneity, which has troubled former studies, without being affected by the problem of low power. Further, we need only assume that unobserved factors are constant during a relatively short time as opposed to fixed effects panel data methods, that typically span many years or even decades.

Our approach leaves two problems remaining, however. Since taking a loan is of course not a source of exogenous variation, the reason the firm takes the loan and the information event around the loan may also affect volatility directly and not only through its effect on leverage. We find that taking a bank loan indeed leads to a large and very significant increase in variance. A part of this increase is transitory and one part is permanent, or at least very long-lived. We attribute the long-lived increase to the change in leverage, since this theoretically should have a permanent effect, and the transitory part to the information event around the loan. The second problem is that the level of the variance and the probability of taking a loan may be dependent of each other. Since variance tends to revert to the long run mean this would result in us capturing both the time-trend and the effect of the leverage change in our results. To remedy this, we do a difference-in-difference style regression where we calculate the change in the variance of a company before and after the loan, minus the change in the market variance before and after the loan. This decreases the estimated elasticity of variance to leverage from around 0.20 to 0.15, but the results remain significant with t-statistics larger than five. A new loan of average size for a company with average leverage will, according to our results, increase its equity standard deviation by 4.6%. Our results remain robust to different types of loans as well as to the purpose of the loan.

The remainder of the paper will discuss the theoretical and empirical relationship between leverage and variance in section 2, section 3 presents the data whereas section 4 outlines the method. Section 5 presents the results and section 6 concludes.

2 Volatility and leverage

2.1 Theory

To illustrate the expected theoretical relationship between equity volatility and leverage we, for clarity and ease of exposition, largely follow Choi and Richardson (2016) who assume the Black and Scholes (1973) model to hold. However, Engle and Siriwardane (2018) show that the monotonically increasing relationship between leverage and equity variance holds for a wide class of return generating processes including the Heston (1993) model with stochastic volatility, and also for models with both stochastic volatility and jumps. The Black and Scholes (1973) relationship between equity variance, leverage, and asset volatility is given by the following equation

$$\sigma_E^2 = \left(\frac{A}{E} N(d_1)\right)^2 \sigma_A^2 \qquad (1)$$

With $d_1 = \frac{\ln\left(\frac{A}{K}\right) + \left(r + 0.5\sigma_A^2\right)T}{\sigma_A \sqrt{T}}$, N is the Gaussian cumulative distribution function, r is the risk-free rate of interest, A is the market value of total assets, E is the market value of equity, K is the book value of debt, whereas σ_E and σ_A are the volatilities of equity and assets respectively and T the maturity of debt[45]. The economic interpretation of $N(d_1)$ is the (risk neutral) probability that the company will not go into bankruptcy at time T. We can also write equation (1) in log form as below

$$\ln \sigma_E = \ln\left(\frac{A}{E} N(d_1)\right) + \ln \sigma_A$$

Equation (1) has several potentially important implications that have been ignored in most prior empirical studies. i) leaving out asset volatility, because it is very hard to estimate, from the specification will give an omitted variables bias since asset volatility and leverage are strongly negatively correlated, ii) the relationship between equity volatility and leverage is not linear unless leverage is scaled by $N(d_1)$, since $N(d_1)$ is a non-linear function in leverage[46], iii) it seems preferable to use the log form in regressions since asset volatility then enters

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[45] Note in Choi and Richardson (2016) the formula for d_1 is misprinted as $d_1 = \frac{\ln\left(\frac{A}{K}\right) + r + \sqrt{0.5\sigma_A^2 T}}{\sigma_A \sqrt{T}}$

[46] Or equivalently the log of $N(d_1)$ should be added as an additional regressor to avoid omitted variables bias since the level of leverage and $N(d_1)$ are negatively correlated.

additively rather than multiplicatively. Leaving out asset volatility has huge empirical effects as demonstrated in Choi and Richardson (2016), unless one looks at within firm variation as we do in this paper. We investigate the effect of leaving out $N(d_1)$ by plotting the theoretical relationship between equity volatility and leverage in Figure 1 with the term included (left pane) and excluded (right pane). The calculations follow appendix A.2 of Engle and Siriwardane (2018). The non-linearity resulting from leaving out $N(d_1)$ is relatively small for companies with short maturity debt (T=2 years) but for highly levered companies with long maturity debt, there is a pronounced concave shape. The non-linearity will also be more pronounced for higher values of asset volatility (not shown in the figure). However, Choi and Richardson (2016) empirically find the differences to be small if $N(d_1)$ is included as a regressor or not.

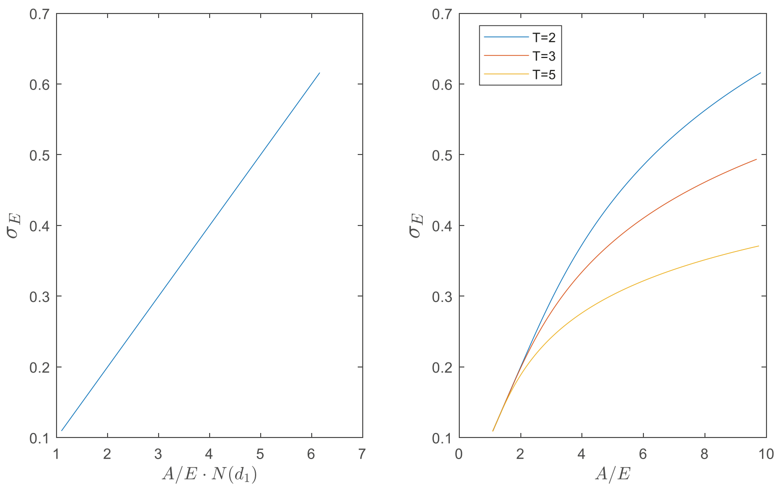

Figure 1 The theoretical relationship between leverage and equity volatility. This figure shows the theoretical relationship between leverage and equity volatility with the term $N(d_1)$ included (left pane) and excluded (right pane). The coefficient values are r=0.03, T={2,3,5}, $\sigma_A^2 = 0.01$.

2.2 Empirics

Firms choose their leverage strategically and firms that are safe in a business sense, i.e. have low asset volatility, will generally pick a high financial leverage obfuscating the true relationship between stock market volatility and leverage, see e.g. Choi and Richardson (2016). Self-selection is of course only a problem when we cannot perfectly control for omitted variables (unobserved heterogeneity) that affects both leverage and equity volatility. It is however extremely hard to control for all potential variables. One example of a difficult-to-measure variable is given in Carvalho (2018) who show that financing constraints, which are of course related to leverage, also affect equity volatility. The strategy to solve the problem of unobserved heterogeneity by including additional control variables, pursued in Choi and Richardson (2016) by adding asset volatility, is hence unlikely to be completely successful. The alternative, to study changes over time for a given firm, by e.g. estimating panel regressions with firm fixed effects, results in low statistical power since a given firm's leverage typically does not change much over time compared to the cross-sectional variation.

Much of the previous literature including Jankensgård and Vilhelmsson (2018), Li et al. (2011), Rubin and Smith (2009), Pástor and Veronesi (2003) as well as Christie (1982) either employ pooled regressions of the form

$$\sigma_{E,i} = \alpha + \beta \left(\frac{A}{E}\right)_i + \boldsymbol{\gamma} Z_i + \epsilon_i \tag{2}$$

or run Fama-MacBeth style regressions which correspond to estimating each cross-section separately and then averaging the estimated coefficients over time. In equation 2 above, β is the coefficient of interest, $\boldsymbol{\gamma}$ is a vector of coefficients and Z_i is a matrix of control variables. It is important to notice that Fama-MacBeth type regressions do not help against unobserved heterogeneity at the firm level. Pástor et al. (2017) show that for balanced panels the Fama-MacBeth estimator is equivalent to a panel regression with *time* fixed effects. Papers using this method typically find an insignificant relationship between equity volatility and leverage. For this method to give an unbiased estimate of the true relationship, we need the very strong assumption that no omitted variables explain both leverage and volatility. This is very unlikely to be true and one of the main points in Choi and Richardson (2016) is that asset volatility has been left out of all studies before their own, which has led to very severe bias in β. Another approach that has not been very common in the literature, one exception is Dennis and Strickland (2004), is to estimate panel data regressions with firm fixed effects of the form

$$\sigma_{E,i,t} = \alpha_i + \beta \left(\frac{A}{E}\right)_{i,t} + \boldsymbol{\gamma} Z_{i,t} + \epsilon_{i,t} \tag{3}$$

with α_i being a firm specific intercept. When firm fixed effects are included, this method is better equipped to deal with unobserved heterogeneity but it still requires that omitted variables are constant over the sample period, which often spans a decade or longer. Another, and maybe more serious, concern is that most of the variation both in equity volatility and leverage is across firms, but panel data regressions with firm fixed effects can only use the within firm variation hence leading to low power to find an effect. Note that estimating the first difference specification

$$\Delta\sigma_{E,i} = \alpha + \beta\left(\Delta\frac{A}{E}\right)_i + \boldsymbol{\gamma}\Delta Z_i + \epsilon_i \tag{4}$$

as done in Choi and Richardson (2016), Li et al. (2011) as well as Bushee and Noe (2000), is equivalent to estimating a panel data regression with firm fixed effects when the number of time periods is two. If potentially omitted variables do not change during the time period, the difference estimator and fixed effects estimator are not biased. Indeed, the results of Table 2 in Choi and Richardson (2016) show the leverage coefficient to be biased downward from 0.61 to 0.06 when the regression is executed in levels, but there is no downward bias from leaving out asset volatility when the regression is based on first differences.

3 Data

Our primary dataset is the newly constructed loan/borrower/lender dataset from Forssbaeck et al. (2018). The unit of observation in the dataset is a loan with loan characteristics from Thomson Reuters/LPC's DealScan database (henceforth DealScan). DealScan provides information on the terms and conditions of deals in the global commercial loan market, including the loan syndication market, and is used in, for example, Ivashina et al. (2015) and Sufi (2007). A syndicated loan is a type of loan offered by a number of banks or financial institutions as opposed to only one lender.

The DealScan data uses its own company identifier, which is not matched with any standard company identifiers such as *cusip* or *permco*. To match companies from DealScan with Capital IQ and Compustat, we use the DealScan to Capital IQ matching from Forssbaeck et al. (2018) and the DealScan-Compustat Link data (updated 2017) of Chava and Roberts (2008). For more details on the construction of the dataset, the reader is referred to Forssbaeck et al. (2018). We extract daily close prices from Compustat/Capital IQ for each company as well as daily high and low prices from CRSP.

We include all loans in the dataset taken by listed US firms from 1988-2016, from both US and foreign banks, in our study. For the event date we use the start date of the loan facility. We define leverage as (*Market value of equity* plus *book value of debt*) / *market value of equity*. This follows the Merton model, except that we use book value instead of market value of debt due to data availability. The change in leverage resulting from the loan is computed as

$$\Delta \text{lev} = \frac{\text{Market cap} + \text{facility amount} + \text{debt}}{\text{Market cap}} - \frac{\text{Market cap} + \text{debt}}{\text{Market cap}} \qquad (5)$$

Market capitalization is calculated on the day of the loan, and the book value of debt on the quarter directly preceding the loan. Facility amount refers to the size of the loan in US dollars.

Table 1 shows that we have a total number of 33,751 loans taken by 19,733 companies. The coverage of DealScan is poor in the start of the sample with very few loans during the late 1980s and early 1990s. The number of loans is around 2,000 per year from the mid 1990s until the start of the financial crisis, and then drops to slightly below 1,000 per year during and after the crisis. The low number of loans in 2016 is because our loan data ends in April 2016. The total loan amount is over 100 billion USD every year after 1992 and the total loan amount over all years is 12.2 trillion USD. The loans are generally big, with an average loan amount of around 200 million during the 1990s and increasing to around one billion towards the end of the sample.

Year	#Companies	#Loans	Total loan amount	Average loan amount
1988	1	1	700	700
1989	45	68	9,418	139
1990	57	109	12,707	117
1991	149	230	43,982	191
1992	286	453	84,922	187
1993	489	845	179,611	213
1994	726	1,181	280,068	237
1995	887	1,536	344,337	224
1996	1,165	2,032	354,012	174
1997	1,413	2,587	576,356	223
1998	1,190	2,193	462,915	211
1999	1,115	2,018	449,573	223
2000	1,061	1,834	495,034	270
2001	1,068	1,806	513,078	284
2002	1,061	1,747	429,040	246
2003	983	1,594	370,865	233
2004	1,010	1,690	565,995	335
2005	921	1,633	639,473	392
2006	825	1,423	739,468	520
2007	779	1,345	760,700	566
2008	519	813	410,373	505
2009	405	602	295,431	491
2010	544	856	437,746	511
2011	788	1,256	835,623	665
2012	572	953	548,732	576
2013	537	961	653,936	680
2014	542	968	755,256	780
2015	485	833	789,735	948
2016	110	184	196,903	1,070
Total	*19,733*	*33,751*	*12,235,989*	

Table 1 Information about the loan data set. The table shows the number of companies, number of loans and the total as well as the average loan amount in million USD from 1988 to April 2016.

Table 2 shows the different types of loans and the different purposes of the loans. Because there are more than 40 distinct loan purpose types in the original data, we follow Forssbaeck et al. (2018) and summarize these into six broader categories: mergers and acquisitions; capital expenditure/investment; general corporate purposes/other; capital structure-related; reorganization (buyout, spinoff etc.); and working capital related. In addition, the DealScan category “debtor-in-possession" is treated as a separate, seventh category, as these firms are undergoing bankruptcy proceedings. The most common loan purpose with 39.5% of the loans is *general corporate purpose* and the second most common with 20.3% is *working capital related*. A small fraction (0.6%) of the loans are *debtor-in-possession* loans and 1.9% of the loans are for *reorganization*. Structural credit models such as Merton (1974) will treat all changes in leverage equally, but since we know the purpose of the loans we can empirically investigate if changes in volatility will depend on the loan purpose.

For the loan types, we again follow Forssbaeck et al. (2018) and construct seven different loan types from the original 63 types in DealScan. The types of loans are Acq./eqm. facility which are acquisition, construction and CAPEX loans, Bridge loans, Fixed-rate notes & bonds, letters of credit, term loans and a category of other loans that cannot be classified into any other category. For this study, the credit lines that constitute 63.6% of all loans are potentially problematic since they give the company the option to draw a variable part of the credit line from zero to 100% of the loan amount. Since DealScan only provides information about the maximum amount, including the credit lines will overestimate the increase in leverage. Because of this, we also do robustness checks that exclude the credit lines from the analysis.

Type of Loan	Number of loans	Fraction of loans
Acq./eqm. facility	481	1.4%
Bridge loan	607	1.8%
Credit line	21,479	63.6%
Fixed-rate notes & bonds	1,185	3.5%
Letter of credit	483	1.4%
Other	601	1.8%
Term loan	8,912	26.4%
Loan purpose	**Number of loans**	**Fraction of loans**
Bankruptcy	211	0.6%
CAPEX	689	2.1%
Cap. structure related	6,502	19.3%
Gen. corp. purp./other	13,333	39.5%
M&A	5,500	16.3%
Reorganization	646	1.9%
Work. cap. related	6,861	20.3%

Table 2 Information about the loan data set. This table presents the loan types and loan purposes defined as in Forssbaeck et al. (2018) and are constructed from a total of 63 original loan type categories and 42 primary loan purposes in DealScan. Bankruptcy are debtor-in-possession loans given to companies in chapter 11, CAPEX is capital expenditure/investment, M&A is mergers and acquisitions, reorganizations include buyouts and spinoffs.

Table 3 presents borrower characteristics. The change in (log) standard deviation before and after the loan is given by $\log(\sigma_{[5,250]}) - \log(\sigma_{[-150,-1]})$, the subscripts give the number of days in relation to the loan, that are used to estimate the standard deviation. The mean increase in log standard deviation after the loan is 0.059. There is a large dispersion between firms with the first percentile at -1.23 and the 99th percentile at 1.45. The average leverage (total assets / total equity) before the loan is 2.36 and the average increase in leverage resulting from the loan is 0.54. The average maturity of a loan is about 49 months with a range from five to 55 months from the 1st to 99th percentile. The companies in the sample have an average market capitalization of above USD6bn, which is considered as relatively large. All accounting variables are winsorized at the 0.5% and 99.5% level.

Variables	Mean	St.dev.	p1	p50	p99	N
$(\sigma_{[-150,-1]})$	56.70	51.50	14.60	43.60	244	33,699
$\log(\sigma_{[5,250]}) - \log(\sigma_{[-150,-1]})$	0.0059	0.47	-1.23	0.025	1.45	33,611
Total assets/total equity	2.36	5.33	1.00	1.39	21.40	30,407
ΔTotal assets/total equity	0.54	1.90	0.0027	0.16	8.05	30,406
Growth total assets	0.0045	0.26	-0.62	-0.0068	1.16	33,388
Market cap.	6,112	22,726	397	680	107,450	30,024
Maturity	48.80	28.10	5	55	120	31,587
Return on assets	1.17	5.39	-20.10	0.00	15.59	33 ,751

Table 3 Descriptive statisticcs of variables. This table presents descriptive statistics for the companies in the sample. All accounting data is measured at the quarter immediately preceding the loan. $(\sigma_{[-150,-1]})$ is the annualized percentage standard deviation calculated using 150 days preceding the loan, $log\ (\sigma_{[5,250]}) - log\ (\sigma_{[-150,-1]})$ is the change in log standard deviation, measured 150 days before the loan until the day before the loan and five days after the loan until 250 days after the loan. Total assets / total equity is the market value of equity plus the book value of debt divided by the market value of equity. ΔTotal assets / Total equity is the increase in leverage resulting from the loan. Market cap is market capitalization in millions of USD. Maturity is the tenure of the loan in months and return on assets uses the definition in Capital IQ, which is the operating income multiplied by 0.625 divided by the average total assets in the two preceding time periods.

4 Method

4.1 Measuring stock return variance

We study total as opposed to idiosyncratic variance for two reasons. First and most importantly, the theoretical relationship between leverage and variance holds for total and not idiosyncratic variance. The second reason is that, empirically, it is typically found that the results differ very little between total and idiosyncratic volatility. For example, Rubin and Smith (2009) find the correlation to be 0.96. Let $r_\mathrm{m} = \mathrm{p_t} - p_{t-m}$ where p is the natural logarithm of the assets' price, denote the continuously compounded m period return and let the unit time period equal one day. Without loss of generality consider the demeaned return generating process $r_{m,t} = \sigma_{m,t} z_{m,t}$ where $\sigma_{m,t}$ is the latent standard deviation and $z_{m,t}$ is white noise with unit variance. Ideally, we would like to observe the latent variance $\sigma_{m,t}^2$ (or standard deviation) but since this is not possible $r_{m,t}^2$ is often used to proxy for $\sigma_{m,t}^2$ with the justification of being an unbiased estimator since

$$E[r_{m,t}^2] = E[\ \sigma_{m,t}^2 z_{m,t}^2] = E[\sigma_{m,t}^2] E[z_{m,t}^2] = \ \sigma_{m,t}^2 \quad (6)$$

While the estimator is unbiased, Andersen and Bollerslev (1998) show the variance in $z_{m,t}$ to be several orders of magnitude larger than the variance in $\sigma_{m,t}$

making an m-period squared return a very noisy estimate of the m-period latent variance. A central result in Andersen and Bollerslev (1998) is that the latent variance can be closely approximated by summing up squared returns of a higher frequency than the time period that variance is measured during. This method of approximating the latent variance is often called realized variance. For a formal treatment of the subject derived from the theory of quadratic variation see Andersen et al. (2005).

Based on the realized volatility literature we therefore construct our m-day variance measure as

$$RV_{[0,m]} = \frac{250}{m}\sum_{t=1}^{m} r_{t,m}^2 \tag{7}$$

with $r_{t,m} = p_i - p_{i-1}$ being a daily return and zero denoting the day of the event. All reported standard variations are scaled by $100\sqrt{250/m}$ so that they can be interpreted as yearly annual standard deviations, assuming 250 trading days in a calendar year.

An alternative to the realized variance estimator is the realized range estimator proposed by e.g. Christensen and Podolskij (2007) that estimates the variance for the range (difference) between the highest and lowest stock price during a time interval. For the same return frequency, the realized range estimator has a variance that is about five time smaller than the realized variance estimator. The realized range-based estimator is defined as follows (Martens and van Dijk (2006))

$$RRV_{[0,m]} = \frac{1}{4\ln(2)}\sum_{i=1}^{m} s_{i,m}^2 \tag{8}$$

with $s = p_i^{high} - p_i^{low}$. Since the high and low prices of the stocks are only available from 2007 in CRSP we use the realized variance estimator for our main results and the RRV estimator for robustness even though it is more efficient.

5 Results

5.1 Event study

To investigate the relationship between volatility and leverage we start by showing that there is indeed a change in volatility after a loan event. We calculate the realized variance for each company before and after the loan was taken and compute the difference in volatility. Since we want to isolate the effect of the loan on the variance, we want to measure the variance during a relatively short time period after the loan, however at the same time, to decrease the statistical uncertainty in the estimate we don't want the number of days (*m*) to be too small. We use a range of values of *m* from 1 to 250 for the period after the loan, and use 150 days in the before period. We have the advantage of having more than 30,000 events and can therefore get good precision in the average effect even when each individual RV is noisy (*m* is low). Algebraically we thus compute the following

$$\Delta RV_{[0,m],i} = \frac{250}{m} RV_{[1,m],i} - \frac{250}{150} RV_{[-150,-1],i}\ , \mathrm{m} = 1, \ldots, 250 \tag{9}$$

with $\frac{250}{m}$ scaling the quantities to annual variances. The average treatment effect of the treated (ATT) for the variance is then defined as

$$ATT_m^{Var} = \frac{1}{N} \sum_{i=1}^{N} \Delta RV_{[0,m],i} \tag{10}$$

with *N* being the number of events. Since the variance estimated with a low *m* has a very large dispersion, especially close to the loan event, we winsorize the variance at the 99.7% level for the variance measure that does not skip any observations after the event[47]. We also calculate the variance in the post event window by skipping the first five observations after the event in order to mitigate the problem of variance induced by increased trading around the event. As seen in Table 4 and Figure 2 there is a large and statistically very significant increase in variance after the loan. As indicated by Figure 2, and the smaller ATT when the first five observations after the loan are skipped, there is one transitory and one permanent, or at least very long lasting, increase in variance.

[47] All the reported differences in Table 4 are highly significant also when no winsorization is done.

The main takeaway from the event study is that an increase in leverage, caused by a bank loan, leads to a large and, importantly, long lasting increase in variance. Theoretically, this finding is not surprising since an increase in leverage should increase variance, but many previous empirical studies relying on cross-sectional regressions, including Jankensgård and Vilhelmsson (2018), Rubin and Smith (2009), Pastor and Veronesi (2003) as well as Bushee and Noe (2000), have either found an insignificant, negative or an economically negligible relationship between equity variance and leverage.

m	$\boldsymbol{ATT_m}$	t-value	$\boldsymbol{ATT_m^{skip\ 5}}$	t-value
5	6,963	13.20	-	-
10	4,569	12.46	3,550	3.75
50	2,051	12.20	2,053	5.84
100	2,074	13.59	2,352	7.44
200	1,886	16.09	2,230	9.89
250	2,100	18.23	2,438	11.92

Table 4 t-tests of difference in variance before and after the loan event. This table presents paired sample t-test of the null hypotheses that the variance and the standard deviation in the period before the loan is equal to that after the loan. The number of days after the event is given by m. For ATT_m , m is also equal to the number of observations used to estimate the variance, for $ATT_m^{Skip\ 5}$ the number of observations equal (m-5). Variances are calculated from daily percentage returns and scaled to annual quantities.

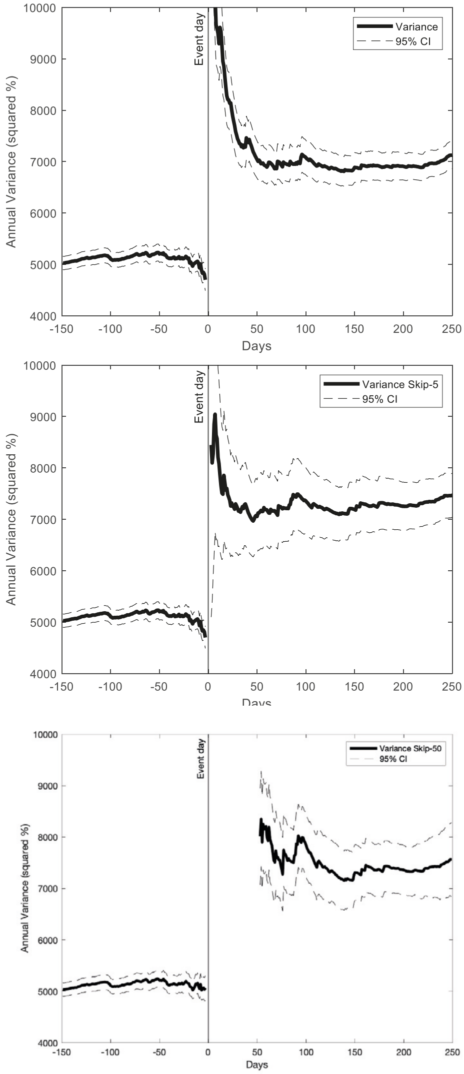

Figure 2 Variance plots. These figures show the average variance expressed as a yearly (squared) percentage standard deviation (solid line) for all firms during the 150-day period prior to the loan event and 250 days after the loan. The number of observations used to calculate each stock's variance is equal to the time period before and after the loan respectively so e.g. one day before the loan a single observation is used, 10 days after the loan 10 observations are used etc. In the first picture, variance is winsorized at the 99.7% level, in the second picture no winsorization is done. In the second picture, the first five observations after the loan event are skipped and in the third picture the 50 first observations after the loan event are skipped The dashed lines show 95% confidence intervals for the average effect.

5.2 The volatility/leverage relationship

Motivated by the theoretical relationship between equity volatility and leverage from structural credit models (see the theory section) we use the change in each company's leverage resulting from the loan to estimate regressions of the form

$$\log(\sigma_{[s,e],i}) - \log(\sigma_{[-150,-1],i}) = \alpha + \beta_1 \Delta\log(\mathrm{lev_i}) + \epsilon_i \tag{11}$$

With *s* and *e* being the start and end days of the window after the loan for which the volatility (σ) is calculated and $\Delta\mathrm{lev_i}$ defined in Equation 5. It may seem like a natural choice to pick *s*=1 however as shown in the event study the change in volatility resulting from the loan seems to have one transitory and one more permanent part. We attribute the transitory part to the information event about the loan that probably leads to increased volatility from increased trading activity. To more cleanly estimate the effect of the leverage change we thus also estimate the regression with values of *s* equal to 5 and 15. The choice of the end day (*e*) is a trade-off between increased precision in the RV estimate from picking *e* high and avoiding other events that may affect the leverage and/or volatility of a company. Because of this, we use several different values for the end date but never less than 50 to capture the long-lasting change in variance.

Table 5 shows that independently of the choice of *s* and *e* we get a positive and highly significant relationship between the change in leverage and the change in variance. Since we use a log specification both for volatility and leverage the coefficient is interpreted as an elasticity. When we use the longest period to measure the after-event volatility (*e*=250) we find an elasticity a bit above 0.2, both when we use all observations (*s*=1) and when we skip the first five or 15 returns after the loan (*s*=5 or *s*=15). The average increase in leverage from a loan is 23%, so the regression results imply that, on average, the standard deviation increases by about 23%*0.2=4.6%. These magnitudes can be compared to untabulated results from estimating the cross-sectional regression in levels which gives an elasticity about 10 times smaller at 0.026, using the same values of *s* and *e* as before. Plosser et al. (1982) show that if a regression is correctly specified (does not have an omittedvariables problem) then, asymptotically, the parameter estimates will be the same from the specification in levels and in first differences. This confirms that also in our sample there are severe problems of omitted variables that almost completely hides the relationship between volatility and leverage if the difference specification is not used.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	s=1	s=1	s=1	s=5	s=5	s=5	s=15	s=15	s=15
Realized variance	e=250	e=100	e=50	e=250	e=100	e=50	e=250	e=100	e=50
Δlog Leverage	0.226***	0.156***	0.129***	0.209***	0.132***	0.094***	0.211***	0.142***	0.094***
	(0.022)	(0.019)	(0.020)	(0.022)	(0.019)	(0.020)	(0.022)	(0.020)	(0.020)
Constant	0.021***	-0.030***	-0.069***	0.019***	-0.036***	-0.076***	0.019***	-0.037***	-0.075***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	30,286	30,312	30,330	30,295	30,319	30,335	30,294	30,323	30,334
R^2	0.006	0.003	0.002	0.005	0.002	0.001	0.005	0.002	0.001
Panel B									
Realized Range									
Δlog Leverage	0.302***	0.183***	0.155***	0.303***	0.190***	0.141***	0.308***	0.211***	0.146***
	(0.045)	(0.037)	(0.036)	(0.045)	(0.038)	(0.037)	(0.046)	(0.040)	(0.037)
Constant	0.002	-0.005	-0.023***	0.001	-0.008	-0.024***	-0.001	-0.010	-0.022**
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
Observations	7,173	7,180	7,181	7,173	7,180	7,181	7,172	7,177	7,180
R^2	0.016	0.007	0.005	0.015	0.007	0.004	0.015	0.008	0.004

Table 5 Regression results. This table displays the regression results from Equation 11, Δlog Leverage is defined according to Equation 5. The dependent variable is the change in variance calculated as $log\ (\sigma_{[s,e],i}) - log\ (\sigma_{[-150,-1],i})$ and estimated using the realized variance estimator in Panel A and the realized range estimator in Panel B. In Panel A the time span is 1988-2016 and in Panel B 2007-2016. Standard errors clustered at the firm level are presented in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ denote significance levels.

When fewer observations are used to calculate the variance after the loan the elasticity of volatility to leverage decreases. This is probably due to the larger measurement error in volatility when fewer observations are used. This explanation is supported by the results from the realized range estimator which has less measurement error and also in all cases a higher estimated elasticity than the realized variance estimator. However, we never get an elasticity that is higher than 0.3 even though the theoretically predicted elasticity is one. Using intraday returns, which we unfortunately do not have access to, would give a more precise variance estimation and may increase the elasticities.

Since we do not have data on asset volatility, we leave out the term $N(d_1)$, which should theoretically result in a concave relationship between volatility and leverage. To test this, we add leverage squared to the specification (results not reported) but this term is very small and insignificant which is in agreement with the empirical results in Choi and Richardson (2016). Since the companies in our sample have a median leverage of 1.39 and the 95th percentile is 4.95 we can also see that the relationship is theoretically very close to linear from Figure 1.

Most companies (80%) have taken more than one loan during our sample period and 21% have taken more than 10 loans. Having the same company several times in the sample may cause dependence in the residuals, and to correct for this all standard errors are clustered on the firm level. It is also possible that the relationship between leverage and volatility is different between companies that take few or many loans. In untabulated results, we find that this is generally not the case; for example, the regression coefficient in specification 1 of Table 5 is 0.226 for the full sample and 0.241 for companies with exactly one loan and 0.269 for companies with <10 loans.

5.3 Controlling for time trends

Since our outcome variable is a single difference over time for the same firm (as opposed to a difference-in-difference) time trends in volatility are a potential problem. We know already since Mandelbrot (1963) that variance is time varying and periods of both high and low variance persist for a while and then slowly mean reverts. If e.g. companies tend to take loans when market volatility is low, the increase in volatility we document could at least partly depend on volatility reverting to a higher level. To control for this, we add the difference in volatility of the SP500 index before and after the loan and estimate regressions of the form

$$\begin{aligned} log\ (\sigma_{[s,e],i}) - log\ (\sigma_{[-150,-1],i}) \\ = \alpha + \beta_1 \Delta\, log(lev_i) + \beta_2 \Delta log\ (\sigma_{[s,e],SP500}) + \epsilon_i \end{aligned} \tag{12}$$

This specification is similar to a standard event study that controls for the market return but our specification is instead for market variance. Note that a difference-in-difference design would be to subtract the change in the SP500 variance from the change in the individual stocks, this corresponds to the special case of the above regression with $\beta_2 = 1$.

Table 6 shows that changes in leverage still have a significant (p<0.001) effect on explaining changes in volatility but the magnitude of the parameters is diminished by about 20-30% depending on the specification. If the dates of the loans had been independent of the level of market wide volatility the estimates should be unaffected so the results indicate that firms tend to take loans when volatility is low. Again, the magnitude of the parameter for leverage is a bit bigger for the realized range estimator.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	s=1	s=1	s=1	s=5	s=5	s=5	s=15	s=15	s=15
Realized variance	e=250	e=100	e=50	e=250	e=100	e=50	e=250	e=100	e=50
Δlog Leverage	0.164***	0.123***	0.113***	0.147***	0.098***	0.076***	0.147***	0.103***	0.072***
	(0.021)	(0.019)	(0.020)	(0.021)	(0.018)	(0.020)	(0.021)	(0.019)	(0.020)
SP500	0.498***	0.450***	0.418***	0.502***	0.459***	0.427***	0.503***	0.468***	0.427***
	(0.011)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Constant	0.004	-0.031***	-0.059***	0.000	-0.038***	-0.067***	0.000	-0.038***	-0.065***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	30,286	30,312	30,330	30,295	30,319	30,335	30,294	30,323	30,334
R^2	0.125	0.105	0.091	0.127	0.112	0.098	0.130	0.121	0.103
Panel B									
Realized Range									
Δlog Leverage	0.172***	0.118***	0.126***	0.174***	0.120***	0.110***	0.179***	0.132***	0.114***
	(0.032)	(0.027)	(0.027)	(0.032)	(0.028)	(0.028)	(0.033)	(0.030)	(0.028)
SP500	0.614***	0.571***	0.551***	0.616***	0.574***	0.556***	0.621***	0.578***	0.559***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
Constant	-0.007	-0.006	-0.009	-0.008	-0.008	-0.011*	-0.008	-0.008	-0.009
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	7,173	7,180	7,181	7,173	7,180	7,181	7,172	7,177	7,180
R^2	0.572	0.573	0.520	0.574	0.578	0.531	0.578	0.586	0.546

Table 6 Regression results. The table displays the regression results from Equation 12 . The dependent variable is the change in variance according to $log\ (\sigma_{[s,e],i}) - log\ (\sigma_{[-150,-1],i})$ and estimated using the realized variance estimator in Panel A and the realized range estimator in Panel B. Δlog Leverage is the change in leverage as given by Equation 5 and SP500 is the difference in the variance of the SP500 index measured in the same way as the individual stock variance. In Panel A the time span is 1988-2016 and in Panel B 2007-2016. Standard errors clustered at the firm level are presented in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ denote significance levels.

5.4 Are all firms and loans created equal?

This section investigates heterogeneity in the change in volatility after the loan depending on firm and loan characteristics as well as on loan purpose. The results are displayed in Table 7. Even though some firm characteristics are significant, the economic impact of the coefficients is very small, a one percent increase in a company's market capitalization leads to a 0.003% decrease in the change in volatility after the loan. Similarly, the impact of asset growth, and the return on assets is very small. When it comes to the purpose of the loan, bankruptcy and reorganization[48], maybe not surprisingly, lead to significantly higher volatility after the loan than CAPEX, which is the baseline comparison. The annual log volatility is 0.181 higher for bankruptcy (the volatility is exp(0.181) = 1.20 % units) for these loans. Column 3 shows that the type of loan has very little effect on the change in volatility. Finally, column 4 shows that the change in leverage is

[48] These are so called debtor-in-possession (dip) loans given to companies in Chapter 11.

still very significant and almost unchanged in magnitude when firm and loan level characteristics are included.

Lastly, we also investigate if the relationship between equity volatility and leverage depends on the level of firm leverage by estimating the regression

$$\begin{aligned} log\ (\sigma_{[5,250],i}) - \log\ (\sigma_{[-150,-1],i}) \\ = \alpha + \beta_1 \Delta\, log(lev_i) + \beta_2 \Delta\, log(lev_i) \cdot lev_i \\ + \beta_3 \Delta \log\ (\sigma_{[5,250],SP500}) + \epsilon_i \end{aligned} \tag{13}$$

Variation depending on the level of leverage will be captured by the interaction term estimated by the β_2 coefficient. We find that the relationship is increasing in leverage with the estimated value of β_2 equal to 0.017 with a t-stat of 6.78. Figure 3 shows the marginal effect of $\Delta\, log(lev_i)$ on the change in volatility for different levels of leverage. Although the effect is increasing in leverage the increase is rather modest in the range between 1 and 5 which corresponds to 95.2% of the observations. Since the marginal effect is small compared to the regression coefficients in Table 6 our results may partly be driven by few companies with very high leverage. To investigate this, we re-estimate specification 1 of Table 6 Panel A twice using only companies that have leverage lower than 10 and 5. When only companies with leverage smaller than 10 are included the elasticity of volatility to leverage decreases from 0.164 to 0.125 (t-stat 6.18) and when only companies with leverage lower than 5 are included to 0.102 (t-stat 4.97). This confirms that the positive and significant relationship exists for all companies and is not driven only by high leverage companies although the effect is larger for high leverage companies.

	(1) s=5, e=250	(2) s=5, e=250	(3) s=5, e=250	(4) s=5, e=250
Growth total assets	-0.023			-0.036
	(0.020)			(0.020)
Market cap (log)	-0.003			0.002
	(0.002)			(0.002)
Loan maturity (log)	0.003			-0.004
	(0.004)			(0.005)
Return on assets	-0.002***			-0.002***
	(0.001)			(0.001)
SP500 vol	0.520***	0.509***	0.511***	0.516***
	(0.011)	(0.011)	(0.012)	(0.011)
Bankruptcy		0.181**		0.232*
		(0.069)		(0.105)
Cap. structure-related		-0.028		-0.028
		(0.023)		(0.026)
Gen. corp. purp./other		-0.018		-0.012
		(0.022)		(0.025)
M&A		0.017		0.027
		(0.024)		(0.026)
Reorganization		0.142*		0.099
		(0.060)		(0.080)
Work. cap.-related		-0.024		-0.018
		(0.023)		(0.025)
Acq./eqm. facility			0.017	0.025
			(0.022)	(0.024)
Bridge loan			0.013	-0.022
			(0.022)	(0.025)
Credit line			-0.014*	-0.010
			(0.006)	(0.006)
Fixed-rate notes & bonds			-0.015	0.001
			(0.016)	(0.019)
Letter of credit			-0.050*	-0.032
			(0.023)	(0.024)
Other			-0.019	-0.054
			(0.029)	(0.043)
Δ log leverage				0.132***
				(0.024)
Constant	0.037	0.042	0.041***	0.022
	(0.020)	(0.022)	(0.006)	(0.030)
Observations	28,149	33,611	33,608	28,148
R^2	0.135	0.122	0.118	0.140

Table 7 Regression results. This table presents results from regressing $log\ (\sigma_{[s,e],i}) - log\ (\sigma_{[-150,-1],i})$ on the log of market capitalization, the log of loan maturity, the return on assets, the SP500 variance, the different loan purposes and the different loan types. For details on loan types and loan purposes, the reader is referred to Table 2. The time span is 1988-2016. Standard errors clustered at the firm level are presented in parenthesis. * p < 0.05, ** p < 0.01, *** p < 0.001 denote significance levels.

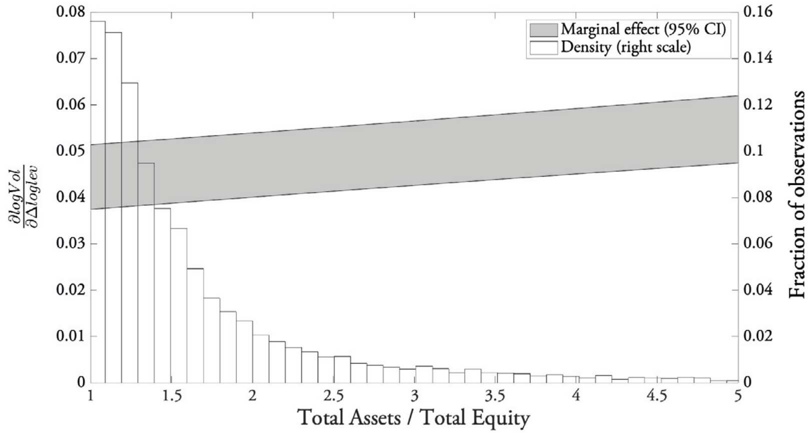

Figure 3 Plot of marginal effects. This figure shows the marginal effect (scale on the left) based on the regression results from equation 13 for different levels of leverage measured by Total assets / Total Equity. The grey shaded area shows a 95% confidence interval for the marginal effect. The histogram in the background shows the distribution of the leverage measure (scale on the right).

5.5 Robustness to loan type and loan purpose

The loan amount for a credit line is given as the maximum amount a company is allowed to draw. Since a company will often use less than the full amount, including credit lines will overestimate the change in leverage. Because of this we do robustness checks in column 1 of Table 8 by dropping all credit lines from the sample. In column 2 we drop all loans that have a primary purpose of reorganization, bankruptcy and M&A since these events may change the asset volatility of the firm. As a last robustness check, in column 3, we only include term loans because these loans are fully funded and drawn at origination. Further, credit facilities are frequently contracted in bundles, known as packages, often consisting of different facility types. Focusing on only term loans eliminates observations on facilities contracted simultaneously within the same package. We find that the relationship between leverage and volatility is remarkably stable across different loan types and loan purposes with the coefficient only changing on the third digit.

	(1) s=5, e=250	(2) s=5, e=250	(3) s=5, e=250
Δ log leverage	0.134***	0.138***	0.139***
	(0.031)	(0.018)	(0.037)
SP500	0.504***	0.501***	0.495***
	(0.019)	(0.008)	(0.020)
Constant	0.010	-0.006	0.013
	(0.007)	(0.004)	(0.008)
Observations	10,756	24,874	7,863
$\mathbf{R^2}$	0.117	0.129	0.118

Table 8 Regression results. This table displays the regression results from Equaton 12. The dependent variable is the change in variance according to $log\ (\sigma_{[s,e],i}) - log\ (\sigma_{[-150,-1],i})$ and estimated using the realized variance. In column one all credit lines are removed from the sample, in column 2 all loans that have a primary purpose of reorganization, bankruptcy and M&A are removed and in column 3 only term loans are included. The time span is 1988-2016. Standard errors clustered at the firm level are presented in parenthesis.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$ denote significance levels.

6 Conclusion

There is a large dispersion in equity volatility across firms and understanding the firm level determinants of stock market volatility is important for many reasons. This paper contributes to our understanding of firm level volatility by studying the relationship between indebtedness (leverage) and equity market volatility, and is the first paper to do so by utilizing loan level data covering a total amount of roughly 12 trillion USD. To investigate the relationship between volatility and leverage we calculate the realized variance for each borrower before and after the loan was taken and compute the difference. We cover more than 30,000 loan events and can hence get good precision in the average effect even when each individual realized variance is noisy. We find clear results that the loan event leads to a large and long lasting increase in equity variance. Since we also know the size of the loans, we can calculate the change in leverage resulting from the loan. We find that for a one per cent increase in leverage, volatility increases by around 0.15-0.30 per cent depending on the time period used to calculate the variance, and depending on if the realized variance or realized range estimator is used. The effect is statistically significant and robust to the type of loan and the purpose of the loan. Theoretically, this finding is not surprising since an increase in leverage should increase variance, but many previous empirical studies relying on cross-sectional regressions have either found an insignificant, negative or an economically negligible relationship between equity variance and leverage.

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What drives Bitcoin volatility?

Byström, H. and Krygier, D.

Abstract

Bitcoin is the world's largest cryptocurrency by market capitalization. Bitcoin is also extremely volatile, and predicting the volatility of any currency or asset is one of the most fundamental tasks for anyone dealing with investment decisions and risk. In this paper we study Bitcoin volatility by looking at the link between the volatility in the Bitcoin market and the volatility in other related traditional markets, as well as the general risk level in the financial system. We also consider retail investor driven search volumes on Google, as a possible proxy for investor sentiment, which has been found to affect price dynamics in financial markets. Our main finding is a relatively strong positive link between Bitcoin volatility and search volumes on Bitcoin-related words on Google, particularly for the search word '*bitcoin*'. Overall, our results point at retail investors, rather than large institutional investors, being the major drivers of Bitcoin volatility.

Key words: Bitcoin, volatility, Google trends, gold, VIX
JEL codes: G10, D80, C80

1 Introduction

One of the most intriguing financial innovations of the last decade is without a doubt the concept of cryptocurrencies. Among the many existing cryptocurrencies, the most well-known one is *Bitcoin*. The market capitalization of the entire cryptocurrency market[49], as of December 2020, is around USD650bn and the Bitcoin market makes up roughly two thirds of that market (Coin-marketcap.com (2020)). The market capitalization of Bitcoin over time is illustrated in Figure 1 below. As is clearly observed from the chart, the market value of all Bitcoins outstanding is currently at an all-time high. Although the Bitcoin market is dwarfed by many traditional financial markets, such as the stock market which has a market capitalization of close to USD100tn or the gold market with a market capitalization somewhere in the USD10tn - USD100tn range, the Bitcoin market is growing quickly. One indicator of the scale of the Bitcoin market is the electricity consumption needed to keep the cryptocurrency market alive. Estimates of the electricity needs vary widely from the energy production of a large nuclear reactor to the energy consumption of a small industrialized country such as Denmark (Bloomberg (2017)).

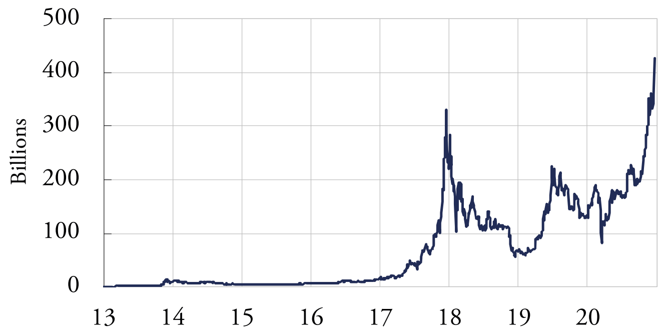

Figure 1 Market capitalization of Bitcoin. The chart illustrates the market capitalization of Bitcoin during the time period 2013-01-01 to 2020-12-18. As of Deceber 2020, market capitalization is at its all time high and amounts to around USD425bn. This number, as implied by the chart, can change a lot and rapidly, during short periods of time.

In this paper we try to answer whether the volatility in the Bitcoin market can be explained by the volatility in traditional financial markets dominated by institutional investors or, perhaps, by internet search activity, which is thought to

[49] Examples of other well-known cryptocurrencies are Ethereum, XRP and Tether.

be created mainly by retail investors and the general public. We also ask whether the Bitcoin volatility perhaps can be explained by the general level of risk in the financial system, as measured by two different risk indicators. In addition to the general academic interest in explaining what drives the price movements in a novel financial market such as the Bitcoin market, there are several practical reasons for looking into this issue. In fact, a range of new innovations in the Bitcoin market highlights the need for more knowledge about causes and features of Bitcoin volatility. One example is the launch in 2015 of a Bitcoin version of the VIX fear index, the so-called .BVOL index, by the Bitcoin derivatives exchange BitMEX (Wong (2014)). The .BVOL index is an index of the volatility in the Bitcoin market, comparable in spirit to the VIX stock volatility index. Another example is the introduction of Bitcoin futures[50], trading on the two derivatives exchanges Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE). To compute the margins required by clearing houses and brokers standing behind the buyers and sellers in such Bitcoin futures markets, one needs to make predictions of the Bitcoin volatility (Financial Times (2017a)). Furthermore, the launch of Bitcoin futures by two of the world's major derivatives exchanges has also led several firms trying to get approval for Bitcoin-tracking exchange traded funds (ETFs) that track futures prices instead of spot prices (Financial Times (2017b)). Currently, there are very few asset classes for which there are no ETFs and an introduction of Bitcoin ETFs could further spur the development of the Bitcoin market. Such a development, with a widening range of potential Bitcoin investors, creates a growing need for a deeper understanding of risk and volatility in the Bitcoin market.

In this paper we look at Bitcoin prices and how the volatility of Bitcoin returns is linked to corresponding volatilities in the gold, currency and stock market, as well as to the general level of risk in the financial system, measured by two market wide risk measures. We also link the Bitcoin volatility to Google internet search volumes on phrases like '*bitcoin*', '*gold price*', '*war*' and '*cyber attack*' using Google Trends. The linkages are studied using daily, weekly and monthly data, and the time period begins in 2011, when a liquid secondary market for Bitcoins had developed, and ends in 2017.

[50] Futures are derivative contracts that oblige the buyer (seller) to buy (sell) an asset at a future point in time for an agreed upon price. The price is typically decided upon entering the agreement and the contract can also be settled in cash, without transferring the underlying asset (if it is tangible).

Correlations and regressions reveal a positive link between contemporaneous changes in Bitcoin volatility and the USD trade weighed currency index volatility (USD volatility from now on). However, the most significant link is found between changes in Bitcoin volatility and search pressures on Bitcoin-related words on Google. To study lead-lag relationships between the variables, and to assess the ability to predict Bitcoin volatilities, we also turn to vector auto-regression analysis and impulse response functions. The results point at Google searches for the word Bitcoin, and to some extent USD volatility, being the only statistically significant determinants of future Bitcoin volatility (changes). Finally, we use our findings to predict Bitcoin volatility out-of-sample. When evaluated using various volatility forecasting evaluation methods we find that, overall, when predicting volatilities in the Bitcoin market it is worthwhile acknowledging search pressure on search engines like Google.

We believe that we contribute to the literature in several ways. First, it is (one of) the first academic studies to look into the causes of the (very high) volatility in the young but quickly growing Bitcoin market.[51] Second, we look at volatilities at different sampling frequencies, with daily, weekly and monthly windows for volatility calculations. Third, by looking at Google search volumes we believe that we can isolate, at least to some degree, the share of the driving forces behind Bitcoin volatility that are related to the retail market. Bitcoin is often regarded as a (merely) speculative tool for retail investors (Financial times (2017c); MotleyFool (2017)) and if it is true that the market behaviour is shaped by these retail investors then there are reasons to believe that the volatility in the market would be primarily caused by retail investors. In fact, the significant positive link that we find between Google search volumes and Bitcoin volatility supports this, i.e. that retail investors, rather than large institutional investors, are the fundamental drivers of Bitcoin volatility. The rest of the paper is organized as follows. In Section 2 we give a brief description of the Bitcoin market and in

[51] The only other similar study of the Bitcoin market that we are aware of is Urquhart (2018), who focuses on “what factors drive the attention of Bitcoin?”. Like us, Urquhart (2018) employs Google Trends data as a proxy for investor attention but then focuses on whether realized volatility (as well as returns or volume) are significant drivers of the attention of Bitcoin. As a side result, however, Urquhart (2018) finds that investor attention offers no significant predictive power in forecasting realized volatility; “the estimation results also reveal that past search queries do not significantly influence realized volatility as the coefficient is only significant at the 10% level”.

Section 3 we review the literature. Section 4 describes the data. In Section 5 we present empirical evidence on the drivers of Bitcoin volatility.

2 Bitcoins and the Bitcoin market

Bitcoin is a cryptocurrency, or more exactly a digital cash peer-to-peer network, that works without a central authority for settlement and validation of currency transactions. Like all cryptocurrencies, Bitcoins have no underlying assets, are not backed by any government and pay neither interest nor dividends. There is no government (i.e. no central bank) backing the currency and Bitcoins are instead issued through a process called mining, where miners provide necessary processing power to the Bitcoin network in exchange for Bitcoins. Bitcoin was introduced in October 2008 by Satoshi Nakamoto[52], which is thought to be an alias, and the key innovation is the way the decentralized Bitcoin network solves the so-called double-spend problem that digital currencies typically suffer from (i.e. preventing a certain Bitcoin to be spent more than once by the current owner). Bitcoin transactions are validated by a network of nodes (the miners) that verify the accuracy of every transaction using previous transactions registered in a ledger called the blockchain. Any new transaction is subsequently added to the blockchain and verified by the entire decentralized network through a concept called proof-of-work (Antonopoulos (2017), Baur and Dimpfl (2017)). Illustrated in Figure 2, approximately 40 million confirmed (and verified) Bitcoin transactions took place during 2019 (Blockchain (2020)). This number can be compared to 138 billion transaction processed on Visa's networks during the same year, or approximately 3700 million card transactions in Sweden (Visa (2020) and Sveriges Riksbank (2020)).

As a result of the mining process, the number of Bitcoins in circulation is steadily increasing. The total number of Bitcoins, however, is capped by the Bitcoin computer algorithm at 21 million, making the Bitcoin deflationary, rather than inflationary like traditional currencies. As of December 2020, approximately 18.5 million Bitcoins are in circulation[53] (i.e. around 80% of the hard-limit total

[52] A paper titled "Bitcoin: A peer-to-peer electronic cash system" was published in 2008 in the public domain.
[53] This number changes approximately every 10 minutes.

money supply which will be reached in year 2140) as illustrated in Figure 2 (Blockchain.com (2018)).

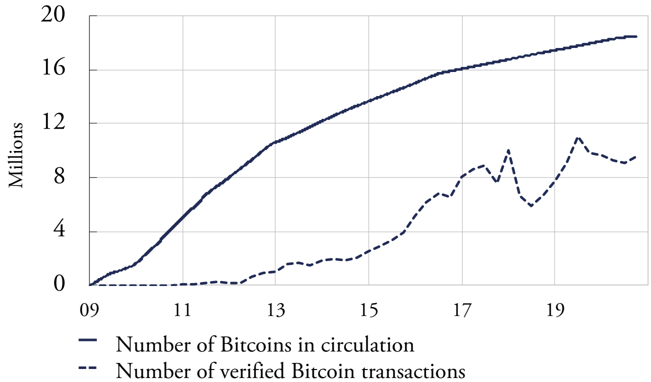

Figure 2 Bitcoins in circulation and transactions. The chart illustrates the total number of mined Bitcoins in circulation (solid line) as well as verified Bitcoin transactions quarterly (dashed line) from 2009-01-01 until 2020-09-30. The total supply is capped at 21 millions and is expected to be reached in year 2140.

The identity of the typical Bitcoin user is not fully known. The encryption technology behind Bitcoin promises the user (more or less) anonymity. According to Yelowitz and Wilson (2015), however, anecdotal evidence puts the Bitcoin user into one of four clienteles; "computer programmer enthusiasts", "speculative investors", "libertarians" and "criminals". Computer wizards are attracted by the possibility to earn money through faster and better mining than their competitors, speculators are tempted by the high volatility of the Bitcoin price, libertarians like the idea of bypassing central authorities such as central banks, and criminals appreciate the near-anonymity of Bitcoin transactions. Yelowitz and Wilson (2015) uses Google Trends to analyze the clientele effect in the Bitcoin market and among the four groups identified above, Yelowitz and Wilson (2015) only find computer enthusiasts and criminals to be behind the (search query) interest in Bitcoin.

A related question is what or who determines the Bitcoin price. Is the price driven by internal forces, i.e. by the Bitcoin market participants themselves? Or by external forces such as macro-variables or prices in other financial markets? Baek and Elbeck (2015) find no significant link between the latter (external fundamental economic factors) and changes in Bitcoin prices, and conclude that Bitcoin returns are driven mainly by the Bitcoin buyers and sellers themselves.

They interpret this as evidence of the Bitcoin market being an early-stage market with highly speculative features.

Further, the status of Bitcoin as an asset has been hard to define – is it a currency or is it a commodity? It has been compared to gold and the US dollar, as it shares many similarities to both assets. Both gold and Bitcoin are costly to obtain, neither of them is controlled by a nation or a government and both assets are extracted through the process of "mining" by independent operators. Gold has long been considered a safe haven asset and a hedging instrument because of its negative correlation with the US dollar. Bitcoin, however, has not typically been recognized as a hedge (Dyhrberg (2016), Bouri et al. (2017)). Similar arguments can be used for the similarity between Bitcoin and the US dollar. Both have no or limited intrinsic value, but while the US dollar is backed by the government Bitcoin is not. Accordingly, some, like Yermack (2015), argue that Bitcoin largely fails to satisfy the criteria for being a fiat currency.

3 Related literature

Few studies have been conducted on the characteristics of Bitcoin volatility; focus has instead been on the price formation and on the main drivers of the price of Bitcoin. Three groups of explanatory variables have typically been used: variables related to investor sentiment and attention, variables related to Bitcoin supply and demand, and variables related to macro-finance. Surprisingly rarely, variables from the various groups have been combined in a single study. Generally, however, empirical research shows that the price formation is due to factors that substantially differ from those affecting conventional assets. Some of these factors include internet search and social media activity (Kristoufek (2013, 2016), Garcia et al. (2014), Kaminski (2014)) as well as Bitcoin trade volume and supply (Balcilar et al. (2017)), with the former being the most studied one. As for volatility, the explanatory power of these factors has been varying, with perhaps internet search and social media activity being the most consistent ones when it comes to both predicting and explaining Bitcoin volatility.

Ciaian et al. (2016) study the Bitcoin price formation by considering both traditional determinants of currency prices and Bitcoin, or digital currency specific factors. They find that market forces of supply and demand, mainly Bitcoin trading volume, number of Bitcoins outstanding and price level, have strong impact on price formation. Further, they find no evidence of the conjecture that macro-financial developments, such as for example stock exchange indices, commodity prices or inflation, should drive the Bitcoin price in either the short or the long run. Kristoufek (2013) investigates the relationship between the Bitcoin price and investors' interest and attention using search queries on Google and Wikipedia as proxies. The study finds a strong correlation between the price and search queries on both internet platforms. However, when prices are above trend, the increasing interest in Bitcoin leads to a continuation of the rise in the price, and the other way around when prices are below trend. This bi-directional, and asymmetric, relationship is argued to be a common sight for financial assets with no underlying fundamentals, such as Bitcoin. In a later paper, Kristoufek (2015) extends the analysis by studying possible fundamental, or economic, drivers, followed by transactional drivers (the use of Bitcoin in real transactions) and technical drivers (the mining process). He finds that Bitcoin behaves according to standard economic theory in the long run, but is prone to bubbles and busts in the short run. From a technical standpoint, when the Bitcoin price increases, users are motivated to start mining. Kristoufek (2015) also finds no signs of Bitcoin being a safe-haven asset, a hypothesis that has been explored also by others (e.g. Shahzad et al. (2010), Bouri et al. (2017), Klein et al. (2018)).

When it comes to Bitcoin volatility, the list of potential drivers that have been tested is more or less the same as the drivers of the Bitcoin price, at least when observing the research output. Bouri el al. (2016) model Bitcoin volatility by applying the asymmetric GARCH model in order to test the impact of positive and negative shocks (news). They do find a positive relationship between shocks to return and volatility, but only in the pre-crash period (up until June 20, 2011 when Mt. Gox was exposed to hackers resulting in a price dip of Bitcoin to 0.01 USD in only a couple of minutes). Bouri et al. (2016) also find a negative relationship between the VIX index and the Bitcoin realized volatility. Dyhrberg (2016) applies the GARCH framework to analyze the behavior of Bitcoin volatility in comparison to gold and the US dollar-euro exchange rate. Similar to gold, the price volatility of Bitcoin also exhibits volatility clustering and high volatility persistence. Dyhrberg (2016) also finds that past volatility as a predictor for future volatility dominates the predictive ability of shock (news) effects for Bitcoin.

A study similar to ours is that of Urquhart (2018) who focuses on "what factors drive the attention of Bitcoin?". Like us, Urquhart (2018) employs Google Trends data as a proxy for investor attention but then focuses on whether realized volatility (as well as returns or volume) are significant drivers of the attention of Bitcoin. As a side result, however, Urquhart (2018) finds that investor attention offers no significant predictive power in forecasting realized volatility. Instead, the previous day volatility and volume, as well as two days previous returns are found as significant drivers of the attention of Bitcoin. This result, assessed during the sample period July 2012 to July 2017, holds, as the author states, from October 2013, but not before. Urquhart suggests that this might be due to the fact that investors are attracted to Bitcoin after increases in volatility and trading volume. Urquhart (2018) studies a time period that ends just one month after ours but compared to us they only look at daily data and US-based Google searches, whereas we look at global searches.

Overall, there is a strong indication that the Bitcoin price and volatility dynamics are influenced by social factors connected to internet search activities. Other currencies and commodities, such as gold and oil, also seem to play a role, perhaps motivated by the finding that Bitcoin is somewhere between being a currency and a commodity. Our paper contributes to the existing literature by combining social factors, general macro-financial risk measures, and volatilities in other traditional financial markets to investigate the driving forces behind the Bitcoin volatility. We believe that an interaction of the said three groups of possible driving forces may be informative when studying the volatility of Bitcoin.

4 Data

The data used in this paper covers the time period August 2011 to June 2017 and all analysis is done on daily, weekly and monthly frequencies.[54] Daily Bitcoin price

[54] The data for the two higher frequencies covers the longest possible single continuous sub-periods that we manage to construct using the Google Trends downloading mechanism (on July 21, 2017). The prices are all end-of-day quotes.

data (USD/Bitcoin) is downloaded from Refinitiv Datastream and is originally sourced from the Luxembourg-based Bitcoin exchange *Bitstamp*. Daily gold price data (USD/Oz), stock price index data (S&P500 Composite Index) as well as USD currency index data (a trade-weighted USD index) are also downloaded from Refinitiv Datastream[55]. The two risk measures, a global economic policy uncertainty index (EPU) and a systemic risk indicator, are from Baker, Bloom and Davis (2016), and the Federal Reserve Bank of Cleveland, respectively. Like the price data described above, the risk measure data covers the time period August 2011 to June 2017 and is sampled on a daily, weekly and monthly frequency (from the daily sampled raw data series).

The *EPU* index is based on three components: nation-wide newspaper coverage frequency of words connected to the economy (E), policy (P) and uncertainty (U), temporary federal tax code provisions that are set to expire within the next 10 years, and disagreement among economic forecasters, where the dispersion between individual forecasters' prediction about future macro-economic variables (such as CPI, local expenditures, state expenditures) is used to construct an uncertainty index about overall policy-related macroeconomic variables. These three components are used to capture overall policy-related economic uncertainty within a country, or globally. Uncertainty indices, such as the *EPU*, have become popular during the recent decade as a tool to evaluate uncertainty in policies related to economic decisions. It is shown in e.g. Rossi et al. (2015), Bali et al. (2017) and Kostka and van Roye (2017) that policy uncertainty is an important factor to take into account when considering any type of asset development and volatility. For a detailed description of the index see Baker, Bloom and Davis (2016).

The systemic risk indicator measures systemic risk in the US banking industry and is provided by the Federal Reserve Bank of Cleveland (originating from Saldías (2013)). The index is based on calculating an insolvency measure, distance to default, that is centered both on individual banking institutions and financial

[55] One might perhaps wonder why the CBOE volatility index, also called the VIX, is not considered in the analysis as it is probably the most popular measure of market sentiment and "riskiness". It is sometimes called the *fear index*. The VIX is a real-time market index that describes the market's expectation of future stock market volatility (30 days). However, it is derived from S&P500 options rather than from stock returns, which is our main argument for not including it in the analysis.

intermediaries, as well as the banking system seen as a whole. The indicator is constructed to gauge market wide perceptions of the risk of widespread insolvency in the banking system and should produce a smooth and informative signal of banking system distress in the long run. Details on the indicator can be found on the website of the Federal Reserve Bank of Cleveland, and in Saldías (2013).

The Google Trends data covers different time periods depending on the sampling frequency due to a downloading limit of the query's time frame. For the daily sampling frequency, the time period is December 21, 2016 – June 19, 2017. For the weekly sampling frequency, the time period is June 24, 2012 – June 18, 2017, and for the monthly sampling frequency the time period is August 2011 – June 2017. The Google Trends search volumes are downloaded (on July 21, 2017) for the nine search strings '*bitcoin*', '*VIX*', '*crisis*', '*cyber attack*', '*gold price*', '*interest rate rise*', '*inflation*', '*stock market crash*' and '*war*'.[56] Google Trends started publicly releasing data on search term intensity in 2009. Rather than providing a measure that portrays the absolute number of searches, the search term intensity is set relative to all other searches over a certain period of time. This means that the relative importance of some words will be different if one would change the sampling time periods. However, by indexing the search interest in this way one controls for any change in the overall internet activity over time. In addition to this indexing set up, the search intensity is also normalized to vary between 0 and 100 where the highest search intensity across the particular time period is set to 100.

Volatilities for the price changes (log returns) of Bitcoins, US stocks, the USD dollar index and gold, are calculated as ordinary weekly or monthly sample standard deviations for the weekly and monthly sampling frequencies (calculated using daily price changes over the week/month) and as squared daily price changes for the daily frequency. That is, all volatilities are estimated using daily observation

[56] Throughout the paper we use the following abbreviations for the various variables: the Bitcoin volatility (BTCVOL), the gold volatility (GOLDVOL), the USD index volatility (USDVOL), the US stock volatility (SP500VOL), the economic policy uncertainty index (EPU), the systemic risk indicator (SYS), Google volume for '*bitcoin'* (GBTC), Google volume for '*VIX'* (GVIX), Google volume for '*crisis'* (GCRISIS), Google volume for '*cyber attack'* (GCYBER), Google volume for '*gold price'* (GGOLD), Google volume for *'interest rate rise'* (GINTE), Google volume for *'inflation'* (GINFL), Google volume for '*stock market crash'* (GCRASH) and Google volume for *'war'* (GWAR).

and, while this is very common in the literature, one must be aware of the fact that, for the daily frequency, a squared daily price change is a noisy measure of true volatility, as can be observed in the first chart of Figure 3. Finally, all Google Trends data is normalized as described above. Figure 3 plots the volatility of Bitcoin, gold, US stocks and the USD trade weighted index, in three charts, for each frequency.

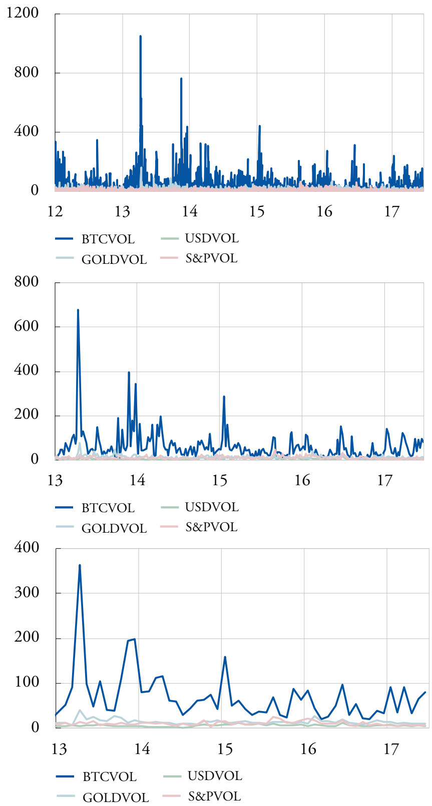

Figure 3 Volatilities of different assets. The three charts above plot the time-series of Bitcoin, gold, S&P500 and the USD trade weighted currency index volatilities on the daily (chart 1), weekly (chart 2) and monthly (chart 3) frequencies. All of the series end in June 2017.

5 Method and results

5.1 Descriptive statistics and correlations

Table 1 reports descriptive statistics for our variables[57]. The first row is for the daily frequency (D), with 128 observations, the second row is for the weekly frequency (W) with 260 observations and the third row of each variable is for the monthly frequency (M) with 70 observation. We observe again that the volatility of Bitcoin is high, at all frequencies, compared to the volatilities on the gold, stock and currency markets. This is, as we know, a well-known stylized fact regularly reported by the media (Financial Times (2018)). Also, the volatility of the volatility itself fluctuates a lot compared to all other variables. The economic policy index (*EPU*), together with most Google search variables, also demonstrate high levels of volatility. The descriptive statistics of the variables vary quite a lot across frequencies, especially regarding skewness and kurtosis. It is the Google search variables in particular that stand out in this regard. Overall, the attributes of each variable vary extensively across variables and within variable groupings (volatilities, risk indicators and Google search terms). Perhaps the least instructive attributes are those of the daily sampling frequency as we, due to Google's extraction procedure, may only extract a very limited time-series. Going forward, we transform the data and use first logarithmic differences of the variables in the analysis (summary statistics of these can be found in the Appendix). Thus, we will be dealing with *percentage changes* between period t and t+1 when analyzing regressions and impulse responses further on in the analysis. The fist logarithmic differencing is executed for stationarity reasons, following e.g. Kristoufek (2013), for all our variables.

We now continue by investigating pairwise correlations between all our variables, for the three frequencies and using the transformed data. Correlations are found in Table 2. Similarly as in Table 1, the first row presents the correlation coefficient for the daily sampling frequency of the variables. Our focus is primarily on the correlations between the Bitcoin price volatility (percent change) and each of the other 14 variables, i.e. the first column in the Table. To start with, we notice that

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[57] Descriptive statistics are tabulated as collected from the source (raw data), i.e. no transformations (apart from volatility calculations) are made. When calculating correlations and estimating regressions we, however, use log first differenced data. Descriptive statistics of the transformed data can be found in the Appendix.

the correlation coefficient rarely reaches levels above +/-0.5. Many correlation coefficients are also close to zero, and insignificant, indicating a non-existing or weak relationship. As for the Bitcoin volatility, the majority of the correlations with the other variables are positive, regardless of frequency. Half of the correlation coefficients are statistically significant, as indicated by the stars in the Table, and most of the significant correlations are positive.

Variable	Obs.	Mean	Std. dev.	Min.	Max.	Skewness	Kurtosis
BTCVOL	128 (D)	53.24	48.28	0.25	237.91	1.19	1.20
	260 (W)	60.30	66.58	4.37	680.50	4.88	35.04
	70 (M)	75.18	60.49	17.25	363.86	2.47	8.11
GOLDVOL	128	8.69	410.45	0.00	37.90	1.25	1.63
	260	13.67	7.66	3.36	78.86	3.29	21.35
	70	15.84	6.77	6.43	43.64	2.12	5.61
USDVOL	128	5.02	4.09	0.00	18.83	1.18	1.28
	260	6.14	3.02	1.49	20.16	1.37	3.32
	70	6.70	2.24	2.04	12.96	0.56	0.45
SP500VOL	128	4.65	4.83	0.00	28.74	1.98	5.30
	260	10.63	6.43	1.45	48.92	1.54	4.52
	70	12.47	5.90	3.98	30.19	1.34	1.53
EPU	128	105.84	44.39	33.16	274.58	1.05	1.68
	260	92.52	48.12	31.98	356.44	1.90	4.99
	70	99.37	44.36	44.56	214.38	1.04	0.18
SYS	128	4.87	0.24	4.54	5.41	0.58	-1.04
	260	5.24	0.87	2.95	7.10	-0.01	-0.69
	70	4.90	1.15	2.16	6.65	-0.60	-0.09
GBTC	128	27.74	15.77	15.00	100.00	1.95	4.02
	260	15.87	13.72	2.00	100.00	2.65	9.06
	70	20.87	20.40	2.00	100.00	2.18	5.50
GVIX	128	51.09	9.57	31.00	100.00	2.64	10.46
	260	42.22	8.98	30.00	100.00	2.15	8.19
	70	53.37	10.29	39.00	100.00	1.66	4.96
GCRISIS	128	75.50	10.66	51.00	100.00	-0.01	-0.05
	260	62.57	9.27	39.00	100.00	0.50	1.21
	70	60.80	7.98	47.00	100.00	0.42	-0.20
GCYBER	128	2.93	11.48	0.00	100.00	7.14	52.76
	260	3.08	8.04	1.00	100.00	9.90	106.04
	70	7.08	12.65	2.00	100.00	6.22	43.21
GGOLD	128	71.19	9.56	57.00	100.00	1.28	1.26
	260	20.69	7.06	14.00	100.00	6.37	62.98
	70	45.27	11.64	32.00	100.00	2.17	6.67
GINTE	128	25.50	14.90	6.00	100.00	2.17	7.29
	260	16.47	9.06	2.00	100.00	3.89	29.08
	70	35.75	15.43	15.00	100.00	1.52	3.76
GINFL	128	75.58	11.15	44.00	100.00	-0.81	0.50
	260	76.17	9.86	49.00	100.00	-0.41	-0.76
	70	75.07	7.99	57.00	100.00	-0.59	-0.46
GCRASH	128	40.70	12.92	15.00	100.00	0.68	2.41
	260	9.48	7.82	3.00	100.00	7.83	80.22
	70	28.55	13.80	11.00	100.00	2.72	10.87
GWAR	128	63.60	7.10	51.00	100.00	1.79	5.35
	260	46.33	7.00	37.00	100.00	3.34	18.81
	70	60.27	7.75	49.00	100.00	2.19	9.08

Table 1 Descriptive statistics of variables. Statistics are based on raw data for all frequencies (daily (128), weekly (260) and monthly (70), covering the period December 2016 to June 2017, June 2012 to June 2017 and August 2011 to June 2017 respectively. The variables ending in *VOL* are volatilities, calculated as squared price changes. *EPU* and *SYS* are the Economic Policy Uncertainty Index (Baker et al. (2016)) and Systemic Risk Indicator (provided by the Cleveland Federal Reserve). The remaining nine variables starting with *G* are Google search strings collected from Google Trends.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
BTCVOL 1	1.00														
GOLDVOL 2	0.15* (D) 0.12* (W) 0.07 (M)	1.00													
USDVOL 3	0.11 0.12 0.33***	0.23** 0.30*** 0.15	1.00												
S&P500VOL 4	-0.08 -0.08 0.06	-0.02 0.25*** 0.38***	-0.07 0.33*** 0.27***	1.00											
EPU 5	-0.11 -0.09 0.03	-0.14 -0.12* 0.27**	-0.04 0.29*** 0.30**	-0.03 -0.26*** -0.19	1.00										
SYS 6	-0.08 0.03 -0.05	-0.09 -0.13** -0.36***	-0.02 -0.04 -0.08	0.00 -0.31*** -0.50***	0.18** -0.20*** -0.31***	1.00									
GBTC 7	0.21** -0.11* 0.56***	0.15 -0.03 0.13	0.19** -0.04 0.05	0.01 0.00 0.03	0.00 0.09 -0.14	0.10 0.04 0.14	1.00								
GVIX 8	0.21** 0.16*** 0.15	0.18** -0.06 0.20*	0.17* 0.03 0.24**	0.13 -0.10 0.49***	-0.17* 0.02 0.33***	-0.20** 0.13** -0.23*	-0.08 0.03 0.09	1.00							
GCRISIS 9	0.18** -0.08 -0.04	0.15 -0.01 0.02	0.11 0.03 -0.22*	0.01 -0.01 0.00	-0.20** 0.05 -0.19	-0.13 0.03 -0.16	0.02 0.09 -0.04	0.42*** 0.21*** -0.07	1.00						
GCYBER 10	0.01 0.08 -0.03	-0.01 -0.13** -0.09	0.28*** -0.01 0.09	-0.07 -0.09 -0.18	0.13 -0.08 -0.06	-0.05 0.12* 0.22*	0.13 0.07 0.21*	-0.18** 0.09 -0.02	-0.11 0.07 0.21*	1.00					
GGOLD 11	-0.21** 0.16** 0.31**	0.07 0.06* 0.58***	0.14 -0.07 0.03	0.09 -0.08 0.07	-0.06 -0.12* 0.05	-0.01 0.10 -0.07	0.14 0.00 0.35***	0.07 0.23*** 0.04	0.01 0.01 -0.03	-0.07 -0.02 -0.02	1.00				
GINTE 12	0.23** -0.14** -0.12	-0.04 -0.11* 0.11	0.03 0.07 0.01	0.09 -0.06 0.16	0.00 0.09 -0.18	-0.04 -0.05 0.05	0.07 0.05 -0.05	0.17* 0.14** 0.12	0.26*** 0.16** 0.17	-0.13 -0.04 -0.07	0.00 -0.01 0.07	1.00			
GINFL 13	0.25*** -0.04 0.08	0.27*** -0.01 0.10	0.29*** 0.00 0.05	0.03 -0.06 0.03	-0.14 0.05 -0.17	-0.06 0.07 -0.02	-0.03 0.08 0.05	0.38*** 0.21*** -0.05	0.65*** 0.58*** 0.56***	-0.06 0.11* 0.13	-0.14 0.04 0.01	0.19** 0.47*** 0.30**	1.00		
GCRASH 14	0.35*** 0.19*** 0.24*	0.29*** 0.05 0.13	0.19** 0.03 0.09	0.10 -0.07 0.39***	-0.15* -0.07 0.13	-0.15* 0.10 -0.10	0.02 0.13* 0.14	0.54*** 0.54*** 0.62***	0.47*** 0.34*** 0.25***	-0.11 0.16*** -0.01	0.12 0.23*** 0.21*	0.13 0.13** 0.14	0.45*** 0.40*** 0.39***	1.00	
GWAR 15	-0.20** -0.12** -0.21	0.06 -0.11* -0.10	0.03 -0.07 -0.29	0.03 0.03 -0.08	0.06 0.02 -0.28**	0.00 0.03 0.00	-0.02 0.04 -0.10	-0.01 0.01 -0.31***	0.08 0.23*** 0.29*	-0.06 -0.02 -0.01	0.30*** 0.11* -0.17	0.02 0.10 0.16	-0.09 0.18*** 0.38***	0.01 0.08 0.00	1.00

Table 2 Correlation matrix. Correlation matrix expressing the pairwise correlation between variables over the sample period December 2016 to June 2017 for all of the frequencies (daily first, weekly second and monthly third on rows). The number of observations is 128, 260 and 70. Correlation is based on variables being expressed in log first differences. The significance level of the correlation coefficient is indicated by * (10%), ** (5%) and *** (1%). The variables ending in *VOL* are time series of volatilities, calculated as squared price changes for the daily frequency. *EPU* and *SYS* are the Economic Policy Uncertainty Index (Baker et al. (2016)) and Systemic Risk Indicator (provided by the Cleveland Federal Reserve). The following nine variables starting with *G* are Google search strings collected from Google Trends.

Among the Google variables, the Google search volume for the word '*bitcoin*' appears to have some importance; the correlation coefficient is statistically significant for all frequencies. At this point we cannot draw any common conclusions regarding the general Google search terms and their correlation with Bitcoin volatility since the correlations are sometimes negative and sometimes positive depending on the frequency of the data. The significance level also varies among the various search terms and frequencies. Overall, however, most of the Google correlations are positive, particularly the statistically significant ones, so there seems to be a positive link (causality not implied) between Google search pressure and Bitcoin price volatility.

As for how the Bitcoin volatility is correlated with volatilities in other markets, we observe that for all frequencies, the volatility of the gold price is positively correlated with the volatility of the Bitcoin price. The correlation coefficient decreases with a declining data frequency (0.15*, 0.12*, 0.07) and is statistically significant for daily and weekly data. The Bitcoin volatility also appears to be positively correlated with the volatility in the US currency market, while the link with the US stock market is inconclusive or non-existing. Overall, the gold price volatility shows the strongest correlation with Bitcoin volatility for our sample period. The two risk measures (*EPU* and *SYS*) show mixed and statistically insignificant results, and we cannot reject the hypothesis that the correlation coefficient between our two (well-known and widely used) risk measures and Bitcoin volatility is zero.

5.2 Regression analysis

The main question that we are trying to answer in this paper is what drives Bitcoin volatility. The simplest way to do this is by regressing Bitcoin volatility on a set of variables that we believe have the potential to explain and, more importantly in a later stage, forecast Bitcoin volatility. Our empirical model is hence a straightforward time series OLS regression model including possible determinants of the volatility in the Bitcoin market.

We begin by conducting unit-root tests on all our variables to make sure that they are all stationary. We start by studying the original data sample, i.e. in levels. For all frequencies, the null hypothesis of an augmented Dickey-Fuller (ADF) unit root test cannot be rejected. This is also the case for the logarithmic transformation of the data. Only when transforming the data by taking the logarithm of the first differences, do ADF tests, as well as simple plots of the data series, show that our variables are stationary. Consequently, all forthcoming analysis is based on logged first-differences of the time series data. This has been a recurring transformation also in previous studies.

We perform a total of six ordinary least squares regressions, two for each data frequency. The first regression for each frequency contains all the variables (at the same point in time), while the second regression also includes (one period) lagged Bitcoin volatility (log difference) on the right hand side since yesterday's value is likely to help predict today's value and as a control for possible autocorrelation in the (logged first difference) Bitcoin volatility. To sum up, we estimate the following two models for each of the three frequencies

$$\begin{aligned} BTCVOL_t = \beta_0 &+ \beta_1 GOLDVOL_t + \beta_2 USDVOL_t + \beta_3 SPVOL_t + \beta_4 EPU_t \\ &+ \beta_5 SYS_t + \beta_6 GBTC_t + \beta_7 GVIX_t + \beta_8 GCRISIS_t \\ &+ \beta_9 GCYBER_t + \beta_{10} GGOLD_t + \beta_{11} GINTE_t \\ &+ \beta_{12} GINFL_t + \beta_{13} GCRASH_t + \beta_{14} GWAR_t + \varepsilon_t \end{aligned} \tag{1}$$

$$\begin{aligned} BTCVOL_t = \beta_0 &+ \beta_1 GOLDVOL_t + \beta_2 USDVOL_t + \beta_3 SPVOL_t + \beta_4 EPU_t \\ &+ \beta_5 SYS_t + \beta_6 GBTC_t + \beta_7 GVIX_t + \beta_8 GCRISIS_t \\ &+ \beta_9 GCYBER_t + \beta_{10} GGOLD_t + \beta_{11} GINTE_t \\ &+ \beta_{12} GINFL_t + \beta_{13} GCRASH_t + \beta_{14} GWAR_t \\ &+ \beta_{15} BTCVOL_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

The Bitcoin volatility is the dependent variable and as explanatory variables we have the gold volatility, the USD currency index volatility, the S&P500 composite stock index volatility, the Economic Policy Uncertainty (*EPU*) index, the systemic risk (*SYS*) indicator from the Federal Reserve, and our nine Google search volume variables: '*bitcoin*', '*VIX*', '*crisis*', '*cyber attack*', '*gold price*', '*interest rate rise*', '*inflation*', '*stock market crash'* and '*war*'.[58] The time period is t=1…T, where the unit of time (and the length of the time-period T) is either one day (T=128), one week (T=260) or one month (T=70) depending on the sampling frequency. In Table 3 we present the results from the OLS regressions. There are

[58] See footnote 56 for the variable abbreviations.

three main columns representing each of the three frequencies, and for each frequency there are two specifications, one excluding and one including the lagged Bitcoin volatility. All through, the regression parameter for the lagged Bitcoin volatility is highly significant and indicates a negative relationship between subsequent Bitcoin volatility changes.

	Daily		Weekly		Monthly	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
GBTC	2.6364**	3.0099***	-0.4267*	-0.2840	1.0105***	0.9912***
	(1.2968)	(1.1344)	(0.2512)	(0.2275)	(0.2056)	(0.1825)
GCRASH	2.5214***	1.9897**	0.3922**	0.2330	0.2959	0.2815
	(0.9598	(0.8436)	(0.1843)	(0.1677)	(0.31457)	(0.2814)
GCRISIS	-3.0805	-1.3695	-1.1842*	-0.8726	0.2324	0.2598
	(2.6404)	(2.3261)	(0.7004)	(0.6347)	(0.7173)	(0.6329)
GCYBER	0.0097	-0.0373	0.0832	0.1201	-0.2348*	-0.2863**
	(0.3479)	(0.3039)	(0.0952)	(0.0861)	(0.125)	(0.1119)
GGOLD	-6.2357**	-2.5973	0.5037	0.6265**	0.5835	0.5841
	(2.7787)	(2.5131)	(0.3212)	(0.2907)	(0.4995)	(0.4455)
GINFL	1.3667	-0.0833	0.2908	0.3902	0.4261	0.6511
	(2.2308)	(1.9654)	(0.8271)	(0.7473)	(1.1398)	(1.0121)
GINTE	0.9365**	0.8423**	-0.3447*	-0.2826*	-0.2559	-0.1711
	(0.4018)	(0.3513)	(0.1783)	(0.1613)	(0.2585)	(0.2356)
GVIX	0.4762	0.5228	0.5316	0.5238	-0.0825	-0.0043
	(1.3090)	(1.1431)	(0.4636)	(0.4187)	(0.6921)	(0.6294)
GWAR	-3.5145	-3.6838	-1.0303	-0.4339	-0.5891	-0.9814
	(2.5903)	(2.2622)	(0.7976)	(0.7248)	(0.7576)	(0.6943)
GOLDVOL	0.0033	-0.0485	0.1166	0.0817	-0.3216	-0.3238
	(0.0940)	(0.0826)	(0.0941)	(0.0853)	(0.2642)	(0.2375)
S&P500VOL	-0.1125	-0.1277	-0.1437*	-0.0553	-0.2192	-0.2168
	(0.1055)	(0.0922)	(0.0829)	(0.0757)	(0.2013)	(0.1842)
USDVOL	0.0069	0.06157	0.2043**	0.1755*	0.8044***	0.6747***
	(0.1387)	(0.1215)	(0.1028)	(0.0929)	(0.2535)	(0.2338)
SYS	-1.9709	-1.3419	-0.6929	-1.2321	-1.3333	-1.4741*
	(7.4448)	(6.5020)	(0.9341)	(0.8461)	(0.9909)	(0.8749)
EPU	-0.3022	-0.1665	-0.1678	-0.2676*	-0.1207	-0.2068
	(0.3194)	0.2800)	(0.1728)	(0.1565)	(0.3210)	(0.2871)
$BTCVOL_{t-1}$	-	-0.4564***	-	-0.4221***	-	-0.3546***
		(0.0821)		(0.0558)		(0.0848)
C	-0.0593	-0.0437	0.0041	0.0060	-0.0238	-0.0290
	(0.1506)	(0.1316)	(0.0512)	(0.0463)	(0.0654)	(0.0586)
R^2	0.2828	0.4588	0.1519	0.3140	0.5237	0.6428
Adj R^2	0.1782	0.3734	0.1034	0.2717	0.4024	0.5417
DW	2.8256	2.3420	2.8268	2.2128	2.7096	2.1237
n	111	110	260	259	70	69
F-stat	0.0022	0.0000	0.0002	0.0000	0.0000	0.0000

Table 3 Regression results. Two OLS models are estimated for each frequency (daily, weekly and monthly). One (even numbered) including one period lagged Bitcoin volatility, and one (odd numbered) without. All variables are expressed in logged first differences and the significance level is indicated by * (10%), ** (5%) and *** (1%). The dependent variable is the (log) change in Bitcoin volatility. The variables ending in *VOL* are time series of volatilities. *EPU* and *SYS* are the Economic Policy Uncertainty Index (Baker et al. 2016) and Systemic Risk Indicator (provided by the Cleveland Federal Reserve). The remaining nine variables starting with *G* are Google search strings collected from Google Trends.

We notice that the Google search term for the word '*bitcoin*' is significant in all specifications except the 4th. The sign of the OLS parameter is not always positive, though, just like for the correlations the OLS-relationship is negative (but not consistently statistically significant) for weekly data. However, similar to the correlations, with data sampled at daily and monthly frequencies, the OLS-relationship between Google search volumes for the word '*bitcoin*' and the Bitcoin volatility is positive and highly significant. Among the other Google search terms, the results again resemble those for the correlations. The relationship is sometimes negative and sometimes positive depending on the frequency of the data. The significance level also varies among the various search terms and frequencies.

As for the link between Bitcoin volatility and the volatility in other more traditional financial markets, Bitcoin volatility is still positively and statistically significantly correlated with the volatility in the US currency market, while the link with volatilities in both the gold and the US stock market is now inconclusive or non-existing. The two risk measures (*EPU* and *SYS*) show a negative relationship with the Bitcoin volatility for all frequencies. The relationship is not statistically significant, however, and we therefore cannot reject the null that there is no relationship between the risk measures and the volatility in the Bitcoin market.

The R^2's are lowest for the weekly frequency. This is possibly linked to the odd results for the Google '*bitcoin*' search term when weekly data is used. Overall, R^2's are higher when lagged Bitcoin volatility is added to the regressions on the right-hand side.

5.3 VARs and impulse response functions

We find no evidence of cointegration among the variables, hence in order to get a dynamic view of how Bitcoin volatility is affected by our variables we estimate an unrestricted vector autoregressive (VAR) model. In a VAR model we model the linear interdependence between multiple time series, where the dependent variable, as well as all the other variables, are regressed on lagged values of themselves, in a system. By doing this, we can study both the contemporaneous effect, and any possible lag effects of the other variables that drive the Bitcoin volatility. We evaluate the estimated VAR models by means of generalized impulse response functions.

We employ a bivariate VAR framework. That is, we estimate a bivariate VAR(p) model (where p is the number of lags) that includes the Bitcoin volatility and each one of the remaining 14 variables, for each frequency. Due to the large number of coefficients to be estimated we chose not to estimate VAR models that have more than two variables at this point. The bivariate choice is also based on the fact that we have a fairly small number of observations relative to the number of coefficients to estimate. This type of modelling, however, still gives us important information, as a complement to the OLS estimations, in the form of tracing out the bivariate relationship dynamics over time. We evaluate the results by estimating generalized impulse response functions that graphically illustrate how the Bitcoin volatility reacts if a given explanatory variable is hit by a shock with a size equal to one standard deviation (in-sample effect).

The number of lags (p) to be included in the VAR models is determined by running a battery of tests.[59] Lag length selection is critical since long lag lengths wastes degrees of freedom and short lag lengths may lead to a misspecification of the model. In total, 6 lags are picked for the daily data, 1-5 lags (depending on the variable) for the weekly data, and 3 lags for the monthly data. All the VAR models are stable, and we have no serial autocorrelation.

We estimate bivariate VAR(p) models, where p is separately determined from the information criteria previously mentioned, and where x_t^i $(i = 1, \dots, 14)$ below represents each of the remaining 14 variables. The number of variables in the VAR(p) model is hence always equal to two, the Bitcoin volatility ($BTCVOL$) and each one of the other 14 variables (x_t^i). The following bivariate system is estimated

$$\begin{aligned} BTCVOL_t = a_{BTC}^0 + a_{11}^1 BTCVOL_{t-1} + \dots + a_{1p}^1 BTCVOL_{t-p} + \; + a_{11}^2 x_{t-1}^i \\ + \dots + a_{1p}^2 x_{t-p}^i + e_{BTCVOL,t} \end{aligned} \quad (3)$$

[59] The tests we use are the likelihood ratio, final prediction error, Akaike, Schwarz and Hannan-Quinn. We use several methods to investigate optimal lag lengths since some of the test-statistics are, for example, sensitive to testing in small samples (such as the likelihood ratio).

where x_t^i is defined as

$$x_t^i = a_{x^i}^0 + a_{21}^2 x_{t-1}^i + \cdots + a_{2p}^2 x_{t-p}^i + a_{21}^1 BTCVOL_{t-1} + \cdots + a_{2p}^1 BTCVOL_{t-p} + e_{x^i.t} \quad (4)$$

As can be seen in Equations 3 and 4, in a VAR(p) model with two variables we get one separate equation for each variable. Each equation then contains p lagged values of itself and p lagged values of the other variables. The resulting $2 \cdot (1 + 2p)$ coefficients are estimated by OLS. After estimation, we confirm that our estimated models are stable by analyzing the inverse roots.

We evaluate the results of our estimated VAR models by means of generalized impulse response functions (first proposed in Koop, Pesaran and Potter (1996) and further developed in Pesaran and Shin (1998)), as we are interested in how the Bitcoin volatility reacts to shocks in one of our other variables at a time. We deviate from the traditional Sims (1980) orthogonalized impulse response functions due to their dependency on the ordering of the variables in the VAR system. We have no way of establishing a clear, or economically motivated, ordering of our variables. We then assess the response of the Bitcoin volatility (expressed in logged first differences) to a positive one standard deviation shock in each of our explanatory variables. The impulse response function shows us the dynamic response to this shock of the Bitcoin volatility variable, with a 95% confidence interval calculated using Monte Carlo methods with 1000 iterations. Preliminarily we may asses the impulse response functions by observing the eigenvalues, or inverse roots, of the VAR systems. All of them are less than unity which means that our VAR models are stable and, accordingly, that the resulting impulse responses should decline over time.

Figures 1a,b-3a,b[60] present 14 impulse response functions (and corresponding accumulated responses) for each of the Bitcoin volatility, when each one of the included variables is shocked (increased) by one standard deviation in the residuals, based on the bivariate VAR models. For many of the variables, the impulse response function indicates a statistically insignificant impact in the first period following the shocks. In the subsequent periods, the response then either

[60] Figures 1a,b are presented here and Figures 2a,b-3a,b can be found in the appendix.

decays or oscillates slowly over time. The only impulse response that is statistically significant for all three data frequencies in the first period is the one for the Google variable *GBTC* (Google search intensity for the word '*bitcoin*'). Again, the response is positive for daily and monthly data but negative for weekly data. The results of the VAR-models and resulting impulse response functions are perhaps expected due to the outcome in the OLS-regressions and no strong evidence of Granger causality among the variables (results not tabulated).

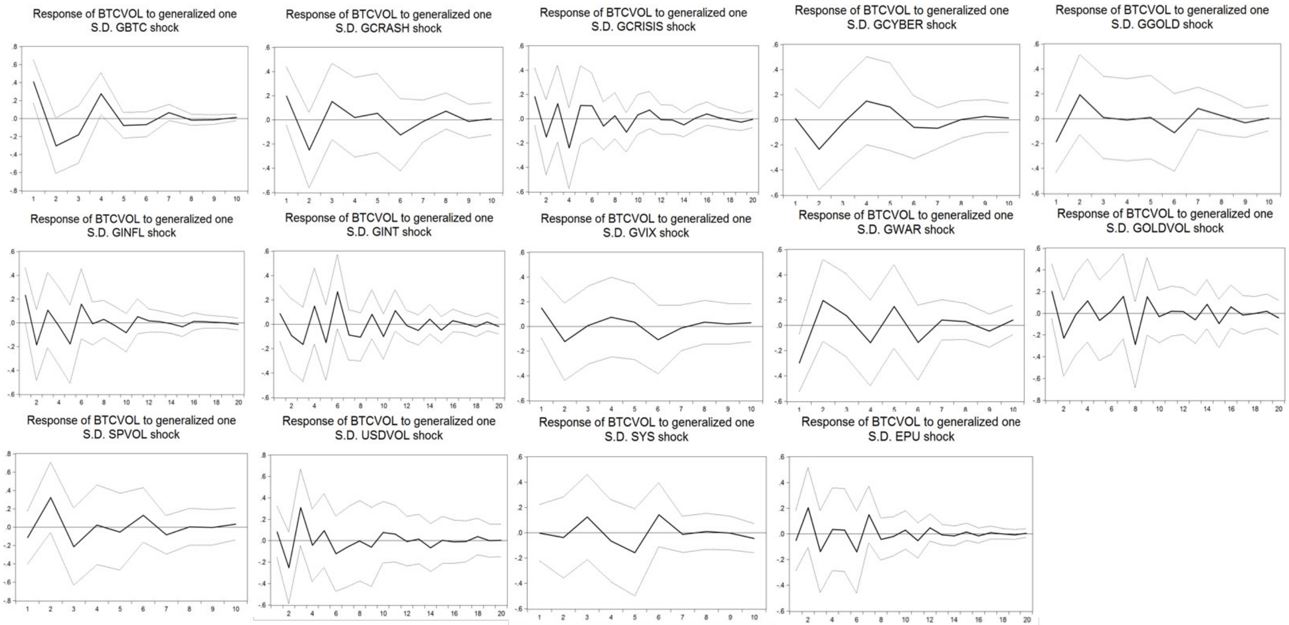

Figure 1a Impulse response functions. Impulse response functions of Bitcoin volatility for the daily frequency, based on data December 2016 to June 2017. One period hence translates into one (trading) day, which is the x-axis. The y-axis corresponds to the logged first difference unit (per cent) of the variable in question. The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock. The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. All of the variables are transformed and expressed in logged first differences. Interpretation of the impulse response goes as follows (top left picture as an example): if daily Googles searches of Bitcoin are being shocked by one standard deviation today, then daily Bitcoin volatility will increase by approximately 0.6 per cent in the first period (day), i.e. tomorrow. As we can see from this example, the increase is statistically significant at the 5% significance level as both dotted lines lie above the x-axis. Impulse responses are derived from bivariate VAR(p) models with a lag length p of 3-7 for all variables. Lag length choices are based on LR, FPE, AIC, SC and HQ criteria. As expected the impulse response goes to zero as time passes; almost directly after period 10 in all of the below impulse response functions. In some figures, the x-axis reaches up to 20 periods. This is only for clarification purposes to ascertain that the impulse response actually does revert over time.

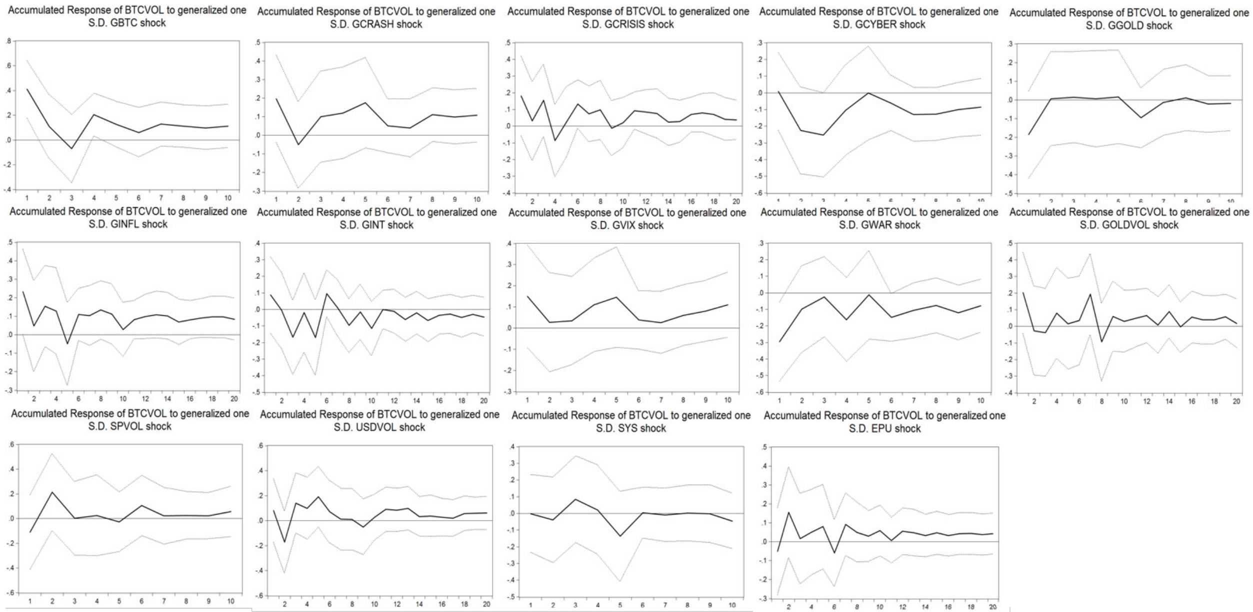

Figure 1b Cumulative response. The corresponding accumulated impulse response of Bitcoin volatility for shocks in all variables, based on figure 1a. As can be seen, in almost no cases is the accumulated response statistically significant. A significant response can only be seen in the Google variable BTC, where in period 1 and 4, the accumulated response at those times is statistically significant on the 5 % level. Dotted lines correspond to a 95% confidence interval.

Observing the impulse response function for the daily frequency in Figure 1a, we see that when *GBTC* is hit by a one standard deviation shock in the residuals, the Bitcoin volatility increases by 0.4% the day following the shock. The accumulated response in Figure 1b, although largely positive across the entire post-period, is not statistically significant. The same applies for the weekly and monthly frequencies in Figures 2-3 with a peak impulse response of, respectively, -0.08% the first week after the shock and 0.3% the first month after the shock. Like for the daily frequency, the accumulated response is overall positive for the entire post-period, albeit not statistically significant, for both the weekly and the monthly frequency.

The only other financial market where a shock to the volatility seems to have an effect on the volatility in the Bitcoin market is the USD currency market. The impulse response is positive for all frequencies and significant for both weekly and monthly data. The result is strongest for monthly volatilities and when the USD volatility is hit by a one standard deviation shock in the residuals, the Bitcoin volatility increases by 0.23% the month following the shock. These findings strengthen the previous results where both correlations and regressions indicate a positive link between volatilities in the two (currency) markets for Bitcoin and the US dollar. The impulse response results point at increased USD volatility spilling over to increased Bitcoin volatility.

In addition to the bivariate VAR-models described above, where all 14 explanatory variables are included one-by-one, we also estimate multivariate VAR models for the subset of explanatory variables that have significant coefficients in the multivariate OLS regression in Section 5.2. These results can be found in Figures 4-6 in the appendix.

For the daily frequency (Figure 4) we estimate a VAR(2) model with five explanatory variables, for the weekly frequency (Figure 5) we estimate a VAR(2) with seven explanatory variables and for the monthly frequency (Figure 6) we estimate a VAR(1) with four explanatory variables. The impulse response results are similar to those for the bivariate VAR estimations in Figure 1. The Google variable *GBTC* again has a more significant and consistent effect on the Bitcoin volatility than the other variables, and, again, the response is positive and statistically significant for daily and monthly data but negative (and insignificant) for weekly data. When the variable *GBTC* is hit by a one standard deviation shock in the residuals, the Bitcoin volatility increases 0.4% (0.35%), respectively, the day (month) following the shock. The effect for the weekly frequency is not significant (-0.06%). These results are essentially the same as those for the bivariate VAR models.

Another more or less unchanged result is that the only other financial market affecting the volatility in the Bitcoin market is the USD currency market. The impulse response is weaker than for the bivariate VAR but it is still positive for all frequencies (i.e. weekly and monthly) where it is included in the multivariate VAR. Like for the bivariate VAR, the result is strongest for monthly volatilities and when the USD volatility is hit by a one standard deviation shock in the residuals, the response of the Bitcoin volatility the first month is 0.25% while the accumulated response is 0.15%.

5.4 Out-of-sample forecasting

The results from the regressions in Section 5.2 can potentially be useful for forecasting purposes. The only variable that is significantly related to Bitcoin volatility, however, is the Google search volume for the word '*bitcoin*'. Through the regressions (Equations 1 and 2) we show that there is a contemporaneous positive *relationship* (causality not implied) between the two variables. The next step is to investigate whether Google can be used to *predict* Bitcoin volatility as well. Being able to forecast the volatility in such a volatile market as the Bitcoin market is, of course, important both in risk management and in trading situations.

As the benchmark predictive models for volatility changes we use two naïve predictors: the *random walk-model*, where the predicted next period volatility is assumed to be unchanged from the current period volatility, and an *AR-model*, where the predicted next period volatility is assumed to be related to the current-period volatility through the auto-regressive relationship in Equation 2. In order to make the most out of our model, which we call the *Google-enhanced model,* we construct the abovementioned predictions using both the current period *GBTC* variable and current period volatility, since these two variables are the only ones that are significant at the 1% level in the OLS-regression (Table 3).[61] Regardless of the model, the predicted future volatility change is transformed to a predicted future volatility (i.e. level) labelled $\sigma_{forecast,t}$ which is then compared to the actual future volatility (i.e. variance). For the forecasting evaluation, the time period is divided into an estimation period (expanding window) and an out-of-sample period. The out-of-sample period is one month for the daily frequency and one year for the weekly and monthly frequencies.

The forecasting performance is assessed using several different loss functions: the root mean squared error (*RMSE*), the percentage squared error (*PSE*), the quasi-likelihood (*QL*) loss function and the *R^2LOG* loss function. These are the loss functions suggested by Brownlees, Engle and Kelly (2011) and Bollerslev, Engle and Nelson (1994) and they are defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(\sigma^2_{\mathrm{realized,t+1}} - \sigma^2_{\mathrm{forecast,t}}\right)^2} \tag{5}$$

$$\mathrm{PSE} = \frac{1}{n}\sum_{1}^{n}\frac{\left(\sigma^2_{\mathrm{realized,t+1}} - \sigma^2_{\mathrm{forecast,t}}\right)^2}{\sigma^4_{\mathrm{forecast,t}}} \tag{6}$$

$$\mathrm{QL} = \frac{1}{n}\sum_{1}^{n}\left(\frac{\sigma^2_{\mathrm{realized,t+1}}}{\sigma^2_{\mathrm{forecast,t}}} - \log\left(\frac{\sigma^2_{\mathrm{realized,t+1}}}{\sigma^2_{\mathrm{forecast,t}}}\right) - 1\right) \tag{7}$$

$$\mathrm{R^2LOG} = \frac{1}{n}\sum_{1}^{n}\left(\log\left(\frac{\sigma^2_{\mathrm{realized,t+1}}}{\sigma^2_{\mathrm{forecast,t}}}\right)\right)^2 \tag{8}$$

Where $\sigma_{forecast,t}$ is the volatility forecast produced at day/week/month *t* of the volatility in day/week/month *t*+1 using information available up to and including day/week/month *t* and $\sigma_{realized,t}$ is the actual *t*+1 volatility.

The forecast evaluations are presented in Table 4 where the Google-enhanced forecasting model, that acknowledges the relationship between search volumes on

[61] The Google-enhanced model is less likely to work for weekly data than for daily or monthly data since no Google search variable is significant at the 1% level for weekly data.

Google for the word '*bitcoin*', is compared to the two benchmark models for the three different forecasting horizons. Like the earlier in-sample results, the results for the weekly data (weekly forecasting horizon) deviates from the daily and monthly results. For the latter two data sets the Google-enhanced model does indeed do a better job in predicting future Bitcoin volatility. For the weekly forecasts, however, the results are worse than for the two benchmark models. As mentioned above, this is not surprising considering the disappointing OLS-regression results for weekly data in Section 5.2.

Daily	**RMSE**	**PSE**	**QL**	**R^2LOG**
Random walk	6013.5825	661.2124	9.6680	1.3071
AR	**4747.3322**	140.9577	4.1145	0.9040
Google	13451.6238	**116.6334**	**4.0754**	**0.8536**
Weekly	**RMSE**	**PSE**	**QL**	**R^2LOG**
Random walk	55893.7095	672.6074	5.8122	0.6172
AR	**55791.8137**	**145.5440**	**3.4649**	**0.4973**
Google	64099.7098	851.8191	6.2606	0.6420
Monthly	**RMSE**	**PSE**	**QL**	**R^2LOG**
Random walk	8308.4612	7.8767	1.4418	0.4445
AR	6325.1436	6.1275	1.1530	0.3065
Google	**4980.1099**	**3.6634**	**0.7220**	**0.1836**

Table 4 Forecast evaluation statistics. Three constructed bitcoin volatility forecast models are evaluated by means of four loss functions: the root mean square error (RMSE), the percentage squared error (PSE), the quasi likelihood (QL) and the R^2LOG loss functions. The three forecast models are a random walk model, where the predicted next-period volatility is assumed to be unchanged from the current period volatility, an AR(1) model (the predicted next period volatility is assumed to be related to the current period volatility through the auto-regressive relationship of order one), and our Google-enhanced model, where an additional predictor, apart from the lagged bitcoin volatility, is the *GBTC*.

Regardless of forecasting horizon, and for every loss function, the most naïve forecasting model, i.e. the random walk-model, demonstrates a worse performance than the slightly more elaborate AR-model which tells us that past volatility changes have predictive power when it comes to forecasting Bitcoin volatility.

For daily and monthly forecasting horizons the enhanced forecasting model dominates the two benchmark models for every loss function except in one single case, the RMSE for daily forecasts. This inconsistency might be linked to the particular features of the Bitcoin market. While the RMSE is widely used in evaluating volatility forecasts, it has some serious drawbacks that are particularly problematic in our case (where the Bitcoin volatility both is very high and very volatile). By construction, for the RMSE, single outliers (large forecast errors) increase the loss function significantly. This could be a problem in cases where one large error is not considered more troublesome than a sum of small errors. If that is the case, one possible solution is to rely on other loss functions, such as the R^2LOG. The R^2LOG also assigns higher weighting to large errors, but less so than the RMSE. The PSE, in turn, focuses on percentage errors and hence controls for the fact that it is harder to be accurate, in an absolute sense, when forecasting in high-volatility regimes. The same goes for the QL loss function. Compared to e.g. the RMSE, the QL loss function therefore makes it easier to compare forecasting ability across volatility regimes.

Overall, though, internet activity seems to be relevant for the behaviour in the Bitcoin market and for anyone who wants to predict volatilities in the Bitcoin market it could pay off to acknowledge search pressure on search engines like Google. However, while this is likely to improve predictions, the improvement is somewhat limited and, as we have shown, also depends on both the forecasting horizon and on how the forecast accuracy is evaluated.

6 Conclusion

In this paper we look at the volatility in the Bitcoin market and how this volatility is related to the volatility in other relevant markets as well as to various market-wide risk indicators. We also investigate whether the volatility in the Bitcoin market is explained by retail investor-driven internet search volumes. The time period is 2011 to 2017 and the analysis is executed on a daily, weekly and monthly frequency. We contribute to the literature in several ways and our results could be of significant practical importance if the Bitcoin market continues to grow at the current speed. Our main finding, based on correlations, OLS-regressions and VAR-analysis, is a fairly strong positive link between Bitcoin volatility changes and search pressure changes on Bitcoin-related words on Google, particularly for the search word “*bitcoin*”. Other than that, the only (somewhat) significant “driver” of Bitcoin volatility changes is the volatility changes in the USD currency market. We further show, using several different loss functions, that Google search activity can be used to make improved predictions of Bitcoin volatility. Overall, internet activity seems to be relevant for the behaviour in the Bitcoin market and for anyone who wants to explain, understand or predict volatilities in the Bitcoin market it could pay off to acknowledge search pressure on search engines like Google. Moreover, the significant link between Google search volumes and Bitcoin volatility points at retail investors, rather than large institutional investors, being major drivers of Bitcoin volatility.

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APPENDIX

Variable	Obs.	Mean	Std. dev.	Min.	Max.	Skewness	Kurtosis
BTCVOL	128 (D)	0.0005	1.7164	-5.7149	4.5757	-0.2206	3.6811
	260 (W)	0.0005	0.8691	-3.3334	2.6025	-0.0075	3.8458
	70 (M)	-0.0066	0.6941	-1.3018	1.3882	-0.0126	2.0721
GOLDVOL	128	0.0313	1.8863	-5.1341	5.1704	-0.2317	3.7972
	260	0.0009	0.5989	-1.4477	1.7277	-0.1119	2.6917
	70	-0.0192	0.3792	-0.6984	1.8478	1.6810	9.9613
USDVOL	128	0.0255	1.2766	-3.0245	4.0038	0.2695	3.4247
	260	-0.0024	0.5654	-1.7049	1.9387	-0.0525	3.0123
	70	-0.0011	0.3060	-0.7137	0.9414	0.3043	3.2740
SP500VOL	128	-0.0249	1.4702	-4.6913	3.3819	-0.0791	3.1996
	260	-0.0061	0.7092	-2.2248	2.7854	-0.1037	4.0483
	70	-0.0180	0.4813	-1.5213	1.3273	-0.1335	3.7557
EPU	128	0.0055	0.5182	-1.1691	1.4985	0.2022	3.4530
	260	-0.0026	0.3269	-1.0729	0.9126	-0.0600	4.0095
	70	-0.0106	0.2512	-0.8241	0.7890	0.0944	4.7892
SYS	128	0.0009	0.0204	-0.0982	0.0696	-0.5967	7.5728
	260	0.0014	0.0596	-0.3717	0.1683	-1.4568	10.0362
	70	0.0115	0.0887	-0.2423	0.2062	-0.5105	3.4490
GBTC	128	0.0075	0.1377	-0.4182	0.4626	0.1772	4.5887
	260	0.0129	0.2085	-0.6931	0.9163	0.7069	6.3837
	70	0.0402	0.3634	-0.9808	1.1939	0.9072	5.5467
GVIX	128	-0.0012	0.1504	-0.4895	0.5293	0.4846	5.5071
	260	0.0110	0.1356	-0.5476	0.6733	0.2247	6.9646
	70	-0.0055	0.1614	-0.5108	0.4220	0.2690	4.3717
GCRISIS	128	0.0001	0.0842	-0.2106	0.2201	0.2137	2.9222
	260	-0.0005	0.0939	-0.4636	0.5447	0.1392	10.2082
	70	-0.0029	0.1241	-0.2829	0.4447	0.4487	4.6414
GCYBER	128	0.0000	0.4629	-0.9555	4.3820	6.5624	65.5548
	260	0.0053	0.5591	-2.6593	3.6109	0.9436	11.9470
	70	0.0374	0.5807	-1.2993	2.8134	1.8574	10.3520
GGOLD	128	-0.0030	0.0602	-0.2458	0.2097	-0.3408	5.5931
	260	0.0006	0.1697	-0.6539	1.5606	3.7104	34.2488
	70	-0.0089	0.1994	-0.4620	1.0217	2.2381	12.8415
GINTE	128	-0.0022	0.4235	-1.3218	1.0986	-0.2342	3.2015
	260	0.0040	0.3394	-1.6607	1.0986	-0.5290	6.0495
	70	0.0048	0.2872	-0.9163	0.9295	-0.1650	4.7834
GINFL	128	0.0009	0.1081	-0.2919	0.3221	0.1343	2.9710
	260	0.0000	0.0901	-0.4177	0.3264	-0.8421	8.2030
	70	-0.0029	0.0892	-0.1780	0.2136	-0.1082	2.6579
GCRASH	128	-0.0015	0.2194	-0.6931	0.6690	-0.1547	3.9575
	260	0.0027	0.3679	-1.8068	1.9021	0.5598	11.5323
	70	-0.0118	0.3759	-1.0046	1.0846	0.0047	4.3101
GWAR	128	-0.0006	0.0610	-0.3011	0.4155	1.6317	22.5964
	260	-0.0003	0.0675	-0.2432	0.2423	0.3899	5.5501
	70	-0.0024	0.1062	-0.4943	0.2107	-1.2171	8.2919

Table 5 Descriptive statistics of variables. Statistics are based on first logarithmic differences for all frequencies (daily (128), weekly (260) and monthly (70), covering the period December 2016 to June 2017, June 2012 to June 2017 and August 2011 to June 2017 respectively. The variables ending in *VOL* are time series of volatilities, calculated as squared price changes for the daily frequency. *EPU* and *SYS* are the Economic Policy Uncertainty Index (Baker et al. (2016)) and Systemic Risk Indicator (provided by the Cleveland Federal Reserve). The following nine variables starting with *G* are Google search strings collected from Google Trends.

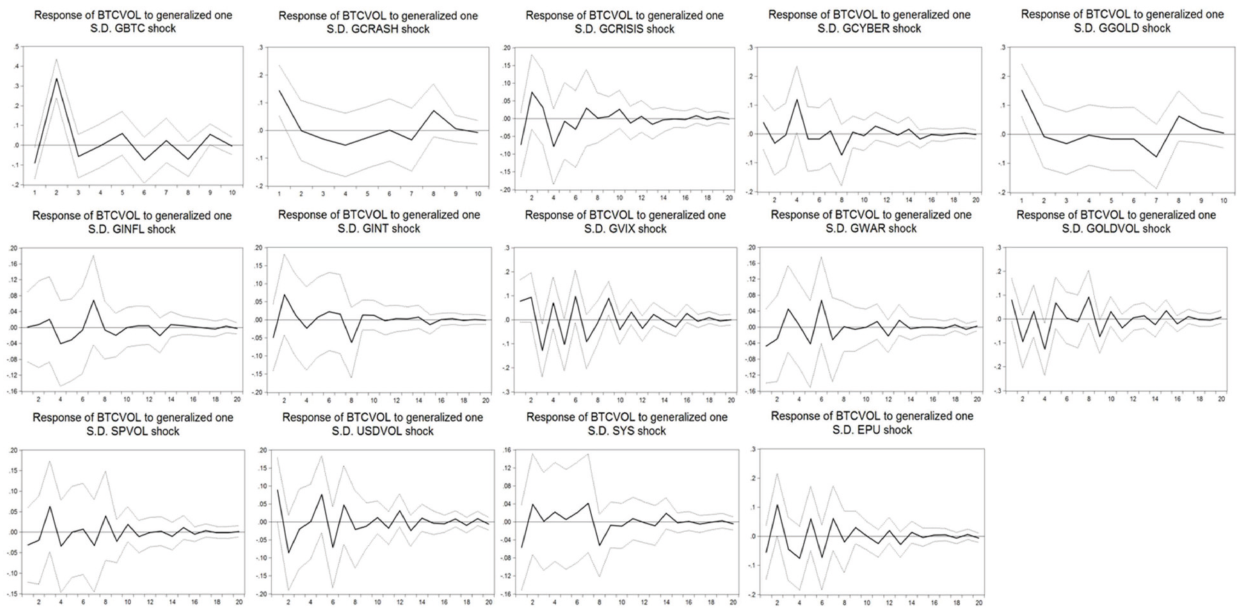

Figure 2a Impulse response functions. Impulse response functions of Bitcoin volatility for the weekly frequency during June 2012 to June 2017. One period hence translates into one week (Mon – Fri), which is the x-axis. The y-axis corresponds to the logged first difference unit of the variable in question. The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock (here called innovation). The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. All of the variables are transformed and expressed in logged first differences. Interpretation of the impulse response goes as follows (top left picture as an example): if weekly Googles searches of Bitcoin are being shocked by one standard deviation, then weekly Bitcoin volatility will decrease by approximately 0.1 per cent (expressed in logged first difference) in the first period (week), and then increase by approximately 0.45 percent in the second period. As we can see from this example, both the decrease and increase seem to be statistically significant on a 5% significance level as both dotted lines lie below (period 1) and above (period 2) the x-axis. Impulse responses are derived from bivariate VAR(6) models. The lag length choice is based on LR, FPE, AIC, SC and HQ criteria. As expected, the impulse response goes to zero as time passes; almost directly after period 10 in all of the below impulse response functions. In some figures, the x-axis reaches up to 20 periods. This is only for clarification purposes to ascertain that the impulse response actually does revert over time.

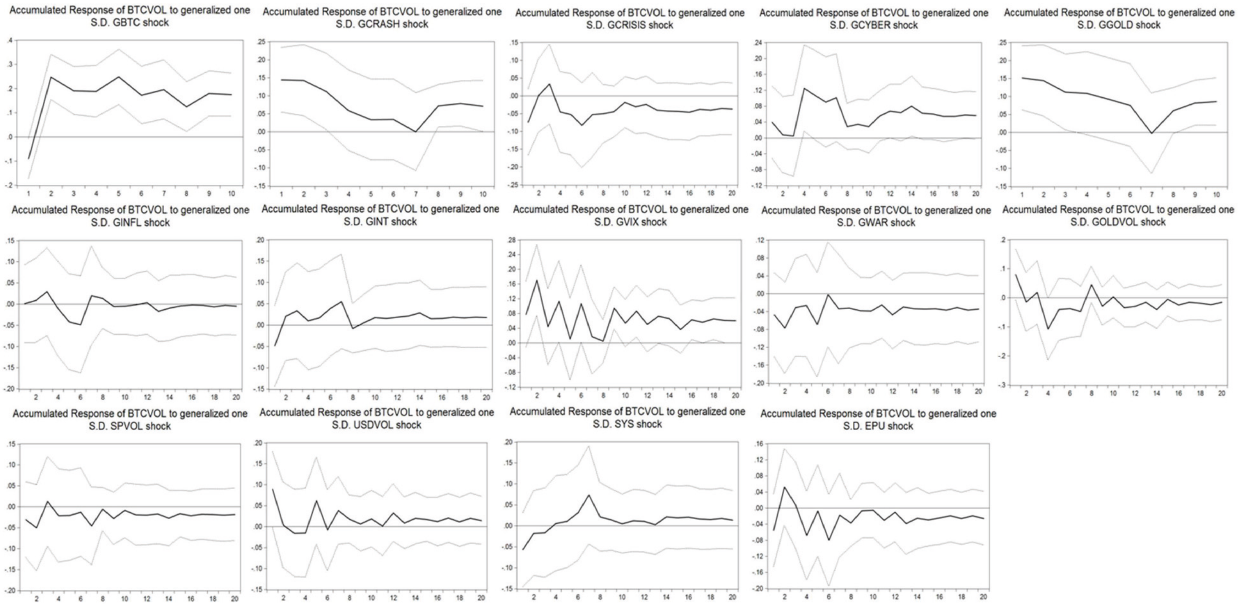

Figure 2b Cumulative response. The corresponding accumulated impulse response of bitcoin volatility for shocks in all variables, based on figure 2a. Dotted lines correspond to a 95% confidence interval. As can be seen, shocks in GBTC, GCRASH, GCYBER, GGOLD and GVIX, almost all Google variables, generate a statistically significant accumulated response in Bitcoin volatility. One period (x-axis) corresponds to one week.

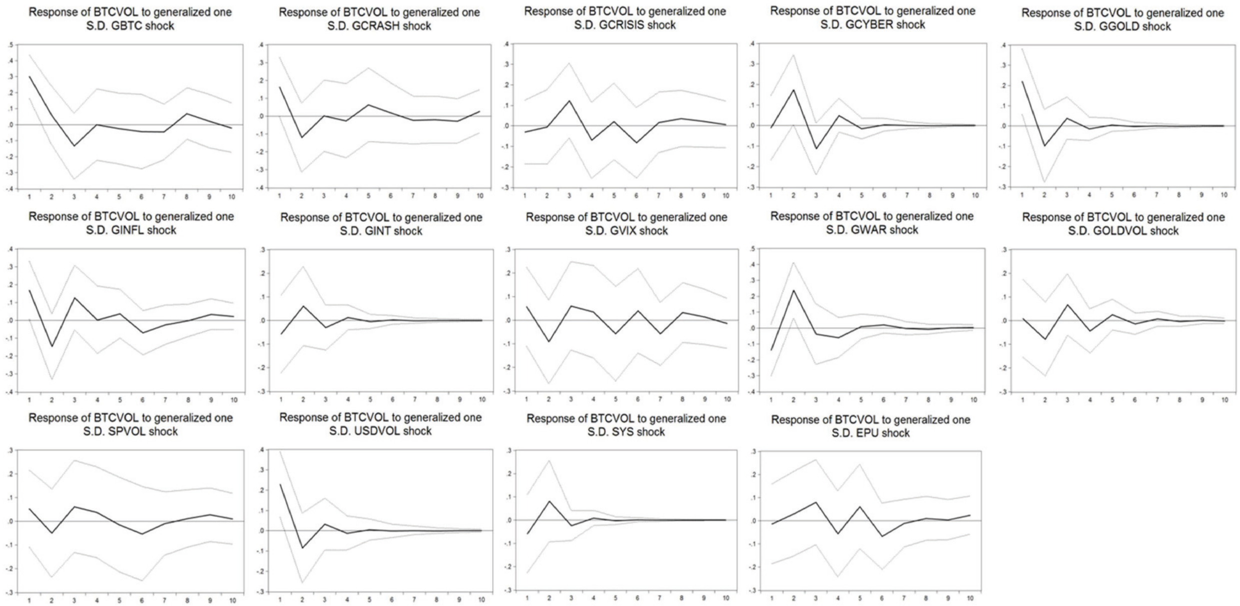

Figure 3a Impulse response functions. Impulse response functions of Bitcoin volatility for the monthly frequency during August 2011 to June 2017. One period hence translates into one month, which is the x- axis. The y-axis corresponds to the logged first difference unit of the variable in question. The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock (here called innovation). The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. All of the variables are transformed and expressed in logged first differences. Interpretation of the impulse response goes as follows (top left picture as an example): if monthly Googles searches of Bitcoin are being shocked by one standard deviation, then monthly Bitcoin volatility will rise by approximately 0.3 per cent (expressed in logged first difference). As we can see from this example, the increase in volatility is also statistically significant on a 5% significance level as both dotted lines lie above the x-axis. Impulse responses are derived from bivariate VAR(p)-models with a lag length p (1 to 5) depending on the variable. Lag length choices are based on LR, FPE, AIC, SC and HQ criteria. As expected, the impulse response goes to zero as times passes; almost directly after period 10 in all of the below impulse response functions.

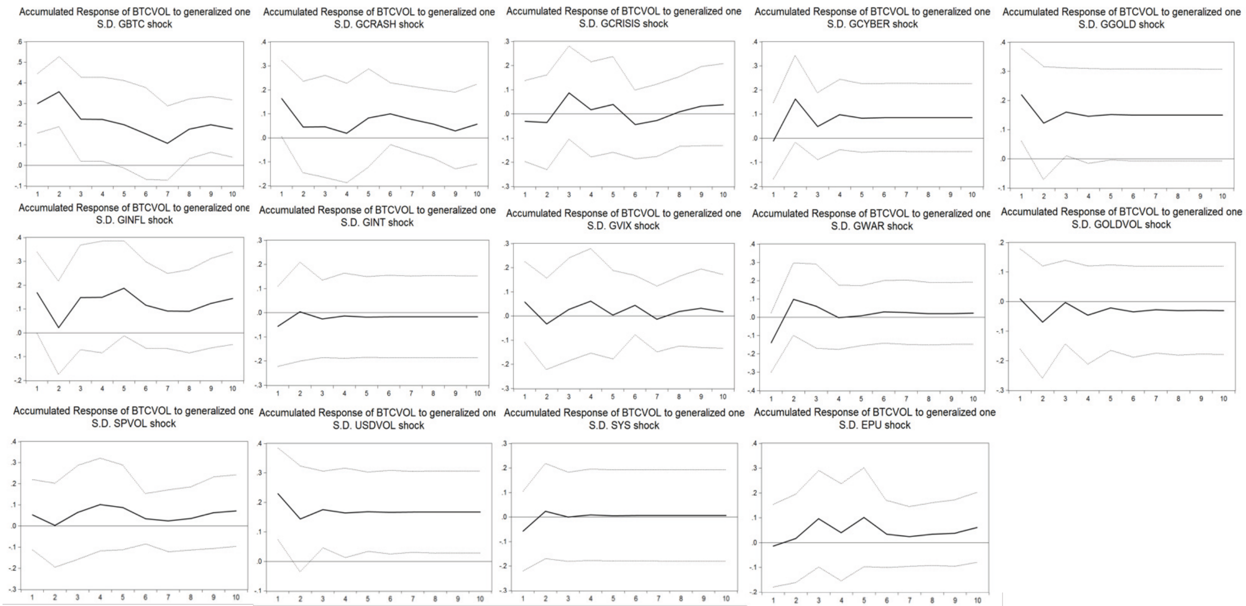

Figure 3b Cumulative response. The corresponding accumulated impulse response of Bitcoin volatility for shocks in all variables, based on figure 3a. Dotted lines correspond to a 95% confidence interval, and one period (x-axis) corresponds to one month. As can be seen from the figures, GBTC, GGOLD and USDVOL generate a statistically significant accumulated response in the Bitcoin volatility variable when they are shocked by one standard deviation. In most cases however, the accumulated response cannot be proven to be different from zero.

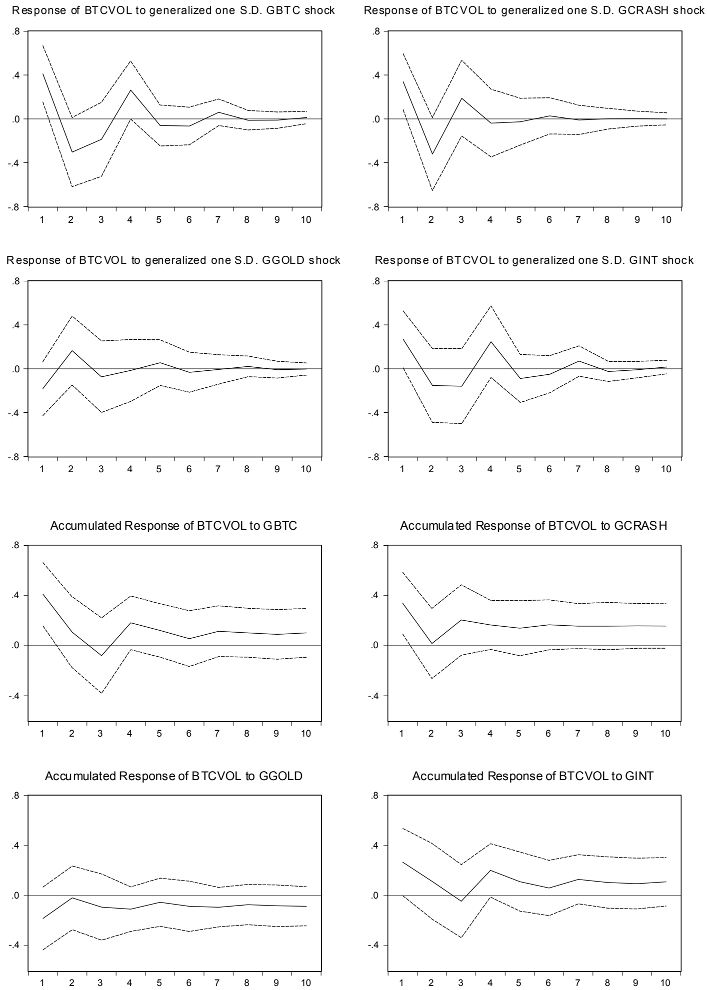

Figure 4 Response and cumulative response. Impulse responses and accumulated responses (second row) of Bitcoin volatility for one standard deviation shocks to the Google variables BTC, Crash, Gold and Interest rate, based on data during December 2016 to June 2017. The x-axis represents the time period, in this case 1 equals one day, the y-axis corresponds to the unit of measurement of the bitcoin volatility (log first difference). The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock. The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. Impulse responses are derived from a VAR(2) model with five variables; the bitcoin volatility and the Google variables BTC, Crash, Gold and Interest rate. The lag length choice is based on LR, FPE, AIC, SC and HQ criteria.

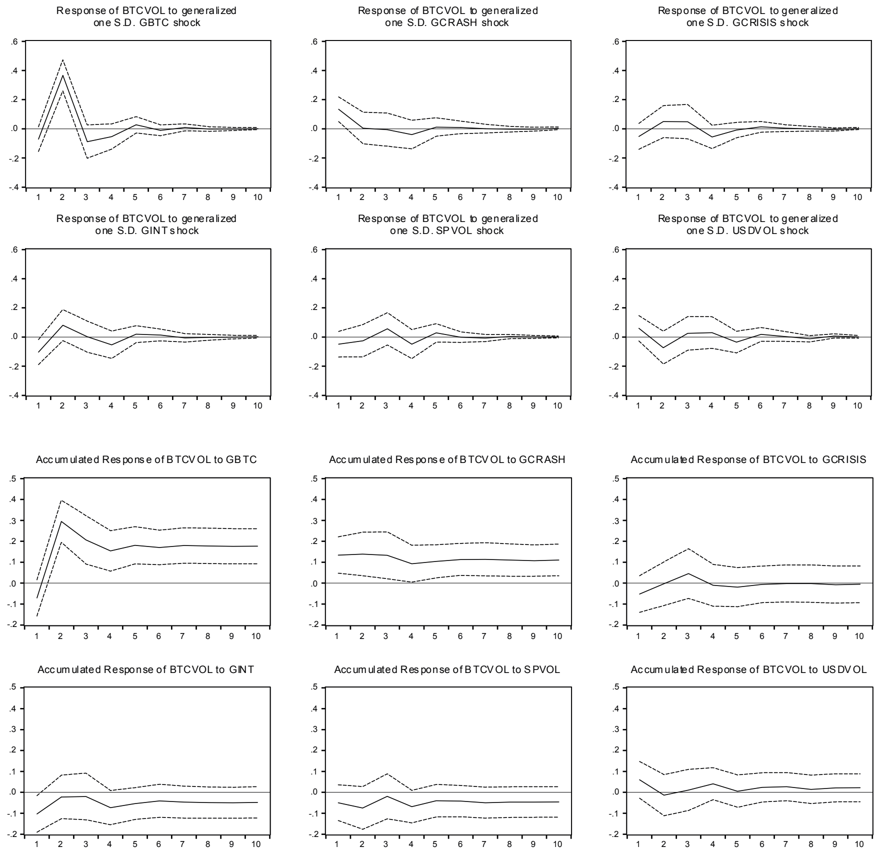

Figure 5 Response and cumulative response. Impulse responses and accumulated responses of Bitcoin volatility for one standard deviation shocks to the Google variables BTC, Crash, Crisis, Interest rate, and the S&P and USD currency index volatilities based on data from June 2012 to June 2017. The x-axis represents the time period, in this case 1 equals one week, the y-axis corresponds to the unit of measurement of the bitcoin volatility (log first difference). The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock. The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. Impulse responses are derived from a VAR(2) model with seven variables; the bitcoin volatility, the Google variables BTC, Crash, Crisis, Interest rate, and the S&P500 volatility and USD currency index volatility. Lag length choices are based on LR, FPE, AIC, SC and HQ criteria.

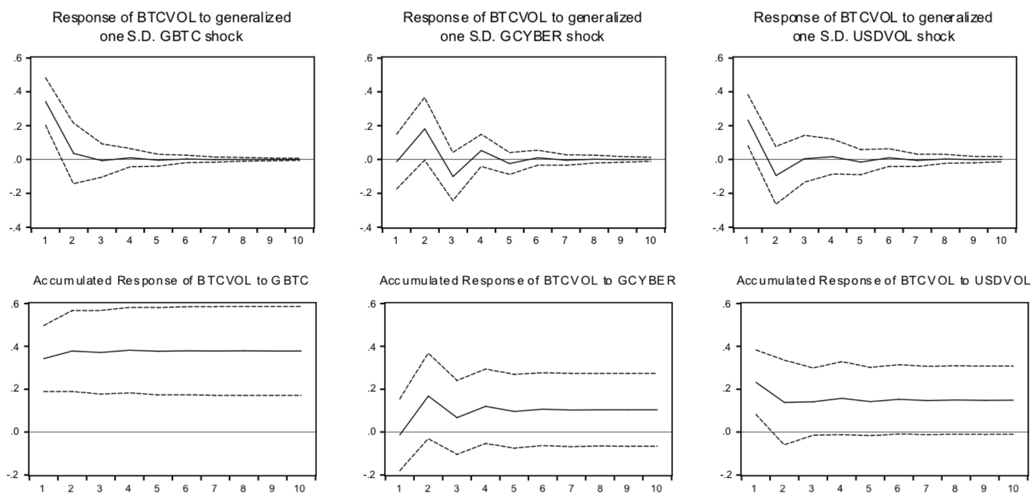

Figure 6 Response and cumulative response. Impulse responses and accumulated responses of Bitcoin volatility for one standard deviation shocks to the Google variable BTC and Cyber, and USD currency index volatility, based on data from August 2011 to June 2017. The x-axis represents the time period, in this case 1 equals one month, the y-axis corresponds to the unit of measurement of the bitcoin volatility (log first difference). The impulse corresponds to a one standard deviation shock to the residuals of the variable that is being hit by a shock. The line corresponds to the response, and the dotted lines indicate a 95 % confidence interval of the response. Impulse responses are derived from a VAR(1) model with four variables; the bitcoin volatility, the Google variable BTC and Cyber, and USD currency index volatility. Lag length choices are based on LR, FPE, AIC, SC and HQ criteria.

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