Are Hedge Funds Still Hidden in the Shadows? An Empirical Analysis of US Banking Regulation

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ABSTRACT

Using quantile regressions, I show that systemic risks arising from US hedge funds cannot be detected in the mean, however exist precisely when the financial system is under stress. Regulators appear to fail in monitoring systemic risks stemming directly from the hedge fund sector, despite a new governing body being introduced as part of the Dodd-Frank Act to specifically oversee it. This is because static risk indicators are used to try identify risks that are dynamic. Regulators have succeeded in suppressing risks from hedge funds that indirectly influence systemic risk through their interactions with the banking sector by placing a ban on bank investment into hedge funds through the Volcker Rule. By using the date that the Volcker Rule was first proposed rather than its actual implementation date, I show that the threat of regulation induced voluntary compliance before it was actually passed. This provides support for the regulation threat hypothesis – that the ex-ante threat of perfect regulation being implemented in the future can be more effective than the actual, ex-post and non-perfect regulation.

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1.0 Introduction

The 2010 Dodd-Frank Act (DFA) brought widespread changes to the US financial system, particularly to the way shadow banks are monitored and regulated. Shadow banking refers to institutions who perform similar functions to that of traditional banks, yet are governed by little or no regulation. Hedge funds are just one subset of this system, and were prone to two major regulatory reforms in 2010 designed to inhibit their impact on financial stability and their interactions with the banking sector in the US. A great difficulty with regulatory design for hedge funds is optimizing the mix of transparency and disclosure that does not hinder financial innovation and competitiveness, while reducing systemic risk (Bianchi and Drew 2014). To the extent that the new regulation has been effective, it would be expected that hedge fund performance now has a weaker relationship with both systemic risk and bank performance. This paper shows that inherent flaws remain in the way systemically risky hedge funds are identified, monitored and regulated.

In 2010, the Financial Stability Oversight Council (FSOC) was introduced as part of the Dodd-Frank Act with the objective of identifying and responding to emerging threats to the US financial system by monitoring non-bank financial companies, including hedge funds. They use thresholds related to size, leverage and interconnectedness to identify funds that can pose a threat to financial stability. The problem with this identification method is that static risk indicators are used to try identify risks in an industry that is invariably dynamic in nature. When identified, the fund is analysed using both public and private information before the Council votes on whether or not it will be supervised by the Board of Governors of the Federal Reserve. By opening itself up to a vote, this process leaves the FSOC prone to lobbying – known to be commonplace in the financial services industry (CNBC 2016). With the aid of a unique dataset that measures total systemic risk (SRISK) in the US, I show that the FSOC

has thus far failed to contain systemic risks arising from large hedge funds – the very hedge funds they try to monitor. I find that the performance of a portfolio containing the largest hedge funds based on deciles is negatively and significantly associated with changes in the level of systemic risk. This relationship holds and is strongest precisely when regulators would find it undesirable. Using quantile regressions – which models the relationship between an independent variable and conditional quantiles/percentiles of the dependant variable rather than the conditional mean – I show that the systemic risks stemming from hedge funds do not exist on average. However, they are extremely high precisely when the financial system is under stress; when changes in the level of SRISK are in the 95th quantile of its distribution. Acharya *et al* (2010) define a systemically risky institution as one that has the propensity to be undercapitalized precisely when the financial system is undercapitalized. If it faces a capital shortage in "normal" times, it may not pose the same threat to financial stability because other institutions can substitute for it and take up its intermediary activities. Given the significant negative relationship between the largest hedge funds' performance and DSRISK when DSRISK is in the 95th quantile of its distribution, large hedge funds thus qualify as systemically important institutions. The presence of this relationship highlights the regulatory failure of the FSOC in supressing the direct transmission of systemic risk by hedge funds.

The Dodd-Frank Act did not fail across the board entirely with its hedge fund regulation. In 2010 the Volcker Rule was first proposed as part of the Act. It bans banks from investing in or sponsoring hedge funds to prevent them from speculating with customer deposits. Initial proposal of the rule led to discord on Wall Street, where banks argued it would be too costly to comply and would affect their bottom line (Financial Times 2014, Business Insider 2011). Despite the backlash, banks prepared for compliance well before the Volcker Rule was actually implemented in April 2014, with Goldman Sachs, Bank of America Merrill Lynch and Morgan Stanley all selling off (or part of) their trading divisions (Fortune 2015, New York Times 2010, The Financial Times 2011). To test if this seemingly

voluntary compliance weakened the relationship between US bank and hedge fund performance, I use the Volcker Rule's initial proposal date to determine if the threat of regulation was effective in thwarting hedge funds' indirect influence on systemic risk through the banking system. A quantile regression analysis shows that bank performance was significantly and negatively related to hedge fund performance when bank returns were in their 75th, 90th and 95th quantiles prior to the Dodd-Frank Act. Following the *proposal* of the Volcker Rule, this relationship changes to positive and significant, with the aggregate effect reducing to almost zero for the 75th, 90th and 95th quantiles. Thus, the threat of regulation that appeared "perfect" in theory achieved its desired effects without actually being passed. This finding can have great implications for regulators, and could offer a new policy tool – the threat of regulation – which is not exposed to potential regulatory arbitrage[1], as regulatory arbitrage cannot take place for regulation that does not yet exist. For the threat of regulation to work, the threat must be credible and create uncertainty for its targets.

The key contribution of this paper is in uncovering the shortcomings of the FSOC in identifying and monitoring hedge funds to limit their capacity to impact systemic risk. Although I acknowledge the difficulties in regulatory design for an industry that is very opaque, the use of static risk indicators to identify risks that are dynamic is confounding, and more must be done by the FSOC to regulate effectively. A second contribution is support for the regulation threat hypothesis – that the threat of perfect regulation being implemented in the future can be more effective than actual, non-perfect regulation. I propose this hypothesis be the centerpoint of future research around financial regulation, as it could serve as an effective policy tool for regulators.

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[1] Regulatory arbitrage refers to the exploitation of loopholes in regulation that is unfavourable to the firm.

The rest of this paper is presented as follows. Section 2 provides a literature review on hedge funds, their interactions with the financial system and the provisions in the Dodd-Frank Act that are to be analysed. Section 3 develops the hypotheses. Section 4 describes the data, variables and the model used to calculate SRISK. Section 5 provides a descriptive analysis to the lay the foundation for the empirical tests. Section 6 tests the success of the Dodd-Frank Act and the Volcker Rule, and provides a discussion of the results throughout. Section 7 outlines the robustness checks undertaken throughout the paper and Section 8 concludes.

2.0 Literature Review

Literature explicitly testing the success of regulation is sparse, particularly for financial regulation[2]. This literature review is structured to introduce hedge funds and describe how and why they can be systemically important. I also outline the key provisions in the 2010 Dodd-Frank Act that are relevant to this study, and finally review literature around the effects of regulatory uncertainty.

2.1 Introduction to Hedge Funds

Hedge funds are sometimes considered as an asset class in themselves, often being labelled as 'alternative investments'. Yet they are far too complex to be considered an asset in their own right, but rather should be considered as an investment vehicle which can provide exposure to many different assets, markets and instruments. They are involved in a range of activities that classifies them under a

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[2] To my knowledge, this is the first paper that empirically tests if the Dodd-Frank Act improved the regulation of hedge funds.

group of institutions known as "shadow banks", who perform similar functions to that of traditional banks, but have very distinguished features. Shadow banks are defined by the US Financial Stability Board (FSB) as institutions that *"intermediate credit outside of or partially outside the banking system, but use leverage and maturity transformation".* Former Federal Reserve Chairman Ben Bernanke offered a slightly different definition; *"shadow banking comprises a diverse set of institutions and markets that carry out traditional banking functions--but do so outside, or in ways only loosely linked to, the traditional system of regulated depository institutions"* (Bernanke 2013)*.* In the context of both definitions, hedge funds are considered as shadow banks as they are involved in credit intermediation, liquidity transformation and maturity transformation (Adrian and Ashcraft 2012). Being a shadow bank means the activities undertaken by these institution is not governed by the same – or any – regulation that the core banking sector adheres to, despite the similarity in functions. A 2010 New York Federal Reserve staff report identified three broad types of shadow banks (Pozsar, et al. 2010):

i) <u>Government-sponsored</u>: shadow banks such as the Federal National Mortgage Association or the Federal Home Loan Bank, which are institutions set up by the government offering mortgage backed securities. Their liabilities are implicitly guaranteed by the Federal Reserve, though they differ from traditional banks as they are funded through capital markets as opposed to deposits. Though not explicitly backed by the government, these institutions qualify as shadow banks as they engage in credit, liquidity and maturity transformation outside the banking system.

(ii) <u>Internal and external</u>: these are regulated institutions who engage in shadow banking activities outside the normal banking system. The internal and external shadow banking systems are differentiated by the origination of funding for off-balance sheet items; internal shadow banks are funded from the US, while external ones are funded from both the US and other countries. Stand-alone broker-dealers, wealth management firms running money market funds, and finance companies such as a car manufacturers' auto loan subsidiary (Adrian and Ashcraft 2012) are examples of internal/external shadow banks.

(iii) <u>Parallel</u>: the parallel shadow banking system (which is what is generally referred in reference to shadow banking) refers to nonbank financial institutions who are not regulated by the government, and engage in shadow banking activities. Investment banks, mortgage lenders and hedge funds are examples of institutions considered to operate in the parallel shadow banking system. They specialize in particular areas of financial intermediation such as low-rated corporate credits, or funding highly rated structured credit assets at cheaper rates than traditional banks. Hedge funds fall under this parallel shadow banking sector. The key feature of shadow banks is that they operate in a looser regulatory environment – "in the shadows" and away from the stringent regulation imposed on the core banking sector.

Hedge funds themselves are opaque investment companies who protect their sophisticated trading and investment strategies to maintain their competitive advantage in a highly competitive industry. They invest in a variety of assets and instruments to generate absolute returns for their investors. They can also act as market makers for financial instruments such as asset-backed commercial paper, asset-backed securities, collateralized debt obligations, and repurchase agreements (Pozsar, et al. 2010). Their field of investments is not restricted, and can include asset classes such as equities, bonds, real estate and currencies among others. They attempt to minimize their risk by hedging themselves against unfavourable market movements. This investment style is complex and involves significant use of derivatives for hedging and speculative purposes, as well as leverage to magnify returns that could otherwise be deemed too low by their investors.

Hedge fund managers have a compensation structure known as "2 and 20"; they receive 2% of AUM annually as a management fee, as well as a 20% share in profits which reduces to zero if there are no profits (Lan, Wang and Yang 2013). This compensation structure is geared to incentivize high performance from fund managers, and is a key differentiator between mutual funds and hedge funds.

Given the excessively high fees relative to other investment vehicles, it seems fair that investors demand high returns. However, funds are aware of this demand and have put in stops to effectively hedge themselves from significant fund outflows and redemptions by introducing lock up periods during which investors cannot withdraw capital. Generally, the length of the lock up period is dependent on the liquidity of the funds' investments; a function of its key investment strategy. Unlike mutual funds, redemptions can only take place periodically (monthly, quarterly or annually, depending on the fund) as opposed to any discretionary day. Investors are well aware of these conditions, as investment into hedge funds is often restricted to those classed as "sophisticated" investors and with a net worth over a certain threshold. They do however, remain protected by the government with respect to fraud and the hedge funds' upkeep of their fiduciary duty to them. This is in stark contrast to the hedge funds themselves, who do not receive federal or state protection in the event of a significant capital decline. By being structured as a limited partnership or limited liability company, hedge funds are able to operate outside of the traditional banking sector and in the "parallel" shadow banking system. While this means no regulatory oversight, no disclosure requirements and no caps on leverage, it reduces the level of investor protection. Note that the shadow banking system refers to financial institutions that intermediate credit, liquidity and maturity transformation, however do not have access to public backstops such as liquidity from the Federal Reserve, or insurance from the Federal Deposit Insurance Corporation (Pozsar, et al. 2010). Some shadow banks do receive government support. Those classed as "government-sponsored" (such as the US Federal National Mortgage Association or the Federal Home Loan Bank in the US) have their liabilities implicitly guaranteed by the Federal Reserve. They differ from traditional banks as they are funded through capital markets as opposed to deposits. Given that hedge funds fall outside of this realm, they forfeit both the benefits of government support as well as the costs of supervision.

The hedge fund industry has attracted significant popularity over the past 30 years, growing to approximately $3.20USD trillion in AUM globally, and $2.28USD trillion in the US alone (Preqin 2016). Popularity of hedge funds in the US has been growing particularly strong, where the domestic industry now accounts for around 71% of total global hedge fund AUM. A defining characteristic that has allowed hedge funds to grow to this size is their extensive use of leverage. The mean leverage ratio across the US – measured as gross assets divided by net assets – was 1.8 as of the third quarter of 2015 (FSOC 2016). Ang, Gorovyy and van Inwegen (2011) found that the mean net leverage ratio among global hedge funds was 0.59, and that mean gross leverage was around 2.10 between December 2004 and October 2009 in the lead up to the GFC. Leverage is used to take advantage of even the smallest mispricing opportunities by magnifying returns that would otherwise not be significant enough to attract further funding from investors. Since leverage ratios are dynamic in response to changing investment opportunity sets, mistiming of markets can have severe consequences for the NAV of a fund. This means that the prominent use of leverage makes the hedge fund industry relevant to systemic risk, either through interactions with its counterparties or through the implications of their failure for \ investors and markets. Not only is leverage important when considering their systemic implications, but so is size. The largest 50 hedge funds were found to control around 31% of gross industry assets in the US, while they also had the highest concentration in leverage during 2015 (FSOC 2016). Their systemic importance stems not only from their characteristics, but also from their role in the market. Many hedge funds are market makers, which gives them a significant role in the movement of asset prices and liquidity provisions (Kruttli, Patton and Ramadorai 2014). This means that their failure can have negative effects on the wealth of individuals and institutions, as well as liquidity provisions in various markets. It makes hedge funds a large market player in both the US and internationally, and as such their performance and characteristics are important for the health of the financial system and the global economy.

2.2 Agency Problems in Hedge Funds

Hedge fund managers are compensated very generously. Their 2 and 20 compensation structure means they have incentive-based compensation on the upside, yet have no consequences for poor performance. This asymmetric reward structure creates a concern for investors, as agency problems can arise through misaligned incentives. Even if hedge fund managers are suffering small losses, an incentive may exist for them to misreport their returns for two reasons; the first is that negative returns tend to lead to investor redemptions. The power of reputation in the hedge fund industry is an important factor in attracting capital, and the combination of low/negative inflows and poor performance leads to hedge fund failure. The second reason is that redemptions lead to drawdowns of AUM and as such, managers earn less with respect to their 2% management fee. Empirical evidence of manager misreporting is mixed. Bollen and Pool (2009) show that a kink exists in the distribution of reported net monthly hedge fund returns around zero. Their pooled distribution suggests that very few hedge funds have small losses, yet many have small profits. They argue this is driven by the manipulation of asset values by managers so that they appear to be making small profits rather than small losses. Given the lack of transparency around hedge funds' portfolios and performance, this kind of behaviour could well be common in the industry. Jorion and Schwarz (2014) argue that this is not direct proof of manipulation, and that the abnormally low amount of hedge funds with small losses is driven by the effect of incentive fees. They show that funds reporting gross returns as opposed to net returns, as well as those without incentive fees, do not exhibit this distribution kink. With the knowledge of this potential incentive misalignment in the industry, it is difficult to accept reported performance as untampered. However, managerial incentives obviously have a positive side for investors. Agarwal, Daniel and Nai (2009) showed that funds with greater managerial incentives are associated with superior performance. They proxy incentives with the levels of managerial ownership, the delta of the option-like incentive fee contracts and the inclusion of high-water mark provisions (when a manager

can only earn incentive fees on profits once previous losses have been covered) in incentive contracts. Superior performance is also associated with longer lockups, notice and redemption periods; all of which proxy for managerial discretion. Despite all this, higher management fees are not related to performance.

The literature shows there is much controversy over how hedge funds report performance, and the implications their reporting can have on future inflows and as such, manager compensation. There is clearly an agency problem between managers and investors; that is their incentives may be aligned with respect to returns, but not necessarily with risk. Because managers must cover previous year losses before getting paid a portion of next years' profits, an incentive exists for them to dissolve quickly and form new funds rather than recovering previous losses (Bali, Brown and Caglayan 2014). This can encourage risky investment as there is little downside risk with respect to manager compensation, yet there is high upside potential. Consider this agency problem in a theoretical context where the investors of a very large hedge fund are comprised of predominantly institutions (such as banks) and a small group of retail investors. The failure of such a fund would have broad systemic implications, particularly if banks were heavily invested in it. Prior to the 2010 introduction of the Dodd-Frank Act where the Volcker Rule was first proposed, there was no regulation surrounding the interaction of banks – who are systemically important institutions – and hedge funds. This means that the failure of a hedge fund could have widespread effects on the financial system, similar to what happened when Long Term Capital Management almost collapsed in 1998. Following the 1997 Asian financial crisis and the 1998 Russian financial crisis, LTCM lost $4.6bn, and had to be bailed out by several large banks such as Merrill Lynch, Morgan Stanley and UBS (among 13 others) in fear of the danger to the financial system that would arise in case of a total collapse. If the hedge fund agency problem is put in this context where its major clients are banks, or banks are forced to bail them out in

case of severe financial distress, it is apparent that hedge funds themselves can be systemically important institutions.

2.3 Bank and Hedge Fund Interactions

While shadow banks and hedge funds operate parallel to the core banking system (Pozsar, et al. 2010), their risks may be intertwined (Chan, et al. 2005, Adrian and Ashcraft 2012). The co-movement of their performance and behaviour can have implications for the financial system, particularly if their performance is highly correlated in periods of market stress. A commercial bank can be exposed to a risk from the hedge fund industry by providing a credit or liquidity line. Conversely, a hedge fund can be exposed to risks from the banking sector by holding substantial positions around stocks in the financial services sector. Exposure of the two sectors to each other has been enabled by the financial innovation and deregulation that has taken place over the past 30 years. As such, the US (and most developed countries) have financial systems comprised of two independently operating 'banking' sectors, yet they are very open and highly integrated.

Although it can be viewed as complement to and not a substitute for the core banking sector, the shadow banking sector has slowly taken on similar roles to that of traditional[3] banks through credit, liquidity and maturity transformation (Noeth and Sengupta 2010). Traditional banks have gone in the opposite direction, transitioning to becoming full service offering institutions with many of them now operating proprietary trading units. This has opened the door for interconnected risk, as losses in one industry may have a contagion effect on the other (Billio et al. 2012, Bianchi & Drew 2014, Chan et al. 2005). Recent blurring of the lines between shadow and core bank functions has made their

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[3] I use 'core banks', 'traditional banks' and 'commercial banks' interchangeably.

interactions an important area of study, particularly given the fact they adhere to different sets of regulation or even non-regulation. Literature acknowledges this shortcoming and has often proposed changes to legislation (Adrian and Shin 2009, Lo 2008, Claessens and Kodres 2014). However, no literature exists in explicitly testing regulatory success for shadow banks, despite ample stress testing on core bank institutions by federal governments.

2.4 Dodd-Frank Act – Overview

On July 21st 2010 the Dodd-Frank Wall Street Reform and Consumer Protection Act (or simply Dodd-Frank Act) was passed by the Obama administration. The Act set up stop measures that would prevent a future sequence of events similar to those that preceded the global financial crisis, with its key goal being to improve financial stability by both monitoring and reducing systemic risks. Reforms were vast and reached most areas of the financial services industry. I identify the key changes to regulation imposed by the Dodd-Frank Act that are relevant to hedge funds, their interactions with the banking sector and their influence on systemic risk (New York Federal Reserve 2010):

i) Reforms of agency oversight:

This saw the introduction of the Financial Stability Oversight Council (FSOC) – among other agencies – which oversees bank holding and nonbank financial companies including hedge funds. It defines nonbank financial companies as a foreign or domestic company that "predominantly engages in financial activities'' and is not a bank holding company. The FSOC's three key objectives (New York Federal Reserve 2010) are:

1. To identify risks to the financial stability of the United States that could arise from the material financial distress or failure, or ongoing activities, of large, interconnected bank holding companies or nonbank financial companies, or that could arise outside the financial services marketplace.

2. To promote market discipline, by eliminating expectations on the part of shareholders, creditors, and counterparties of such companies that the Government will shield them from losses in the event of failure. This refers to being "too big to fail".

3. To respond to emerging threats to the stability of the United States financial system. The Federal Reserve has the power to prohibit proprietary trading, investments and sponsorships of hedge funds by banks, and large financial companies need to submit 'wills' to be used in the case of financial distress.

ii) Stringent regulatory capital requirements:

Supervised nonbank and bank holding companies (BHC's) with $50 billion or more in total consolidated assets are subject to risk-based capital requirements, liquidity requirements, leverage limits and concentration limits. Their D/E ratio is capped at 15-to-1.

iii) The Volcker Rule:

Named after former Federal Reserve Chairman Paul Volcker, the rule prohibits most proprietary trading by banks. It prevents covered institutions from investing, owning or sponsoring hedge funds or private equity funds, and also requires additional capital requirements for nonbank financial institutions engaging in proprietary trading. The rule was first proposed in July 2010 as part of the Dodd-Frank Act, but did not get passed until April 2014 due backlash from large US banks including Goldman Sachs and JP Morgan Chase & Co. Full compliance was required by July 2015 (Practical Law 2015)

iv) Greater investor protection:

The SEC has the power to oversee private funds managed by investment advisers, and offers rewards for whistle-blowers. It also promotes higher fiduciary standards for institutions providing personalized investment services.

The two most relevant provisions from the Dodd-Frank Act are the new Financial Stability Oversight Council, and the Volcker Rule. In Section 2.5 and 2.6, I explain how each works, its key objectives and its desired outcome.

2.5 The Financial Stability Oversight Council

The FSOC was created to improve financial stability in the US. It has access to information from government agencies, other regulators and the Office of Financial Research (an independent bureau within the United States Department of the Treasury) which was introduced in the 2010 Dodd-Frank Act to provide analysis to government agencies. Here, I outline the FSOC's objectives, how it governs and potential drawbacks of its process.

The FSOC's three major objectives are designed to reduce systemic risks that may arise from hedge funds. All objectives refer to sound management of risks created or posed by the hedge fund industry, and as such aim to reduce their capacity to increase financial instability. To do this, it must be able to identify funds that have the potential to undermine financial stability, particularly amid market turmoil (US Department of the Treasury 2015). The identification process of such a hedge fund involves three stages, where progression to the next stage requires that it fulfils certain criteria. Should a fund go through all three stages, it is then put to a vote for council members to decide if it will be monitored by the Board of Governors of the Federal Reserve. The three stages involved in the identification process are:

1. **Stage 1**: narrowing the universe of nonbank financial companies that may be subject to supervision. The FSOC assesses companies with respect to six quantitative thresholds around size, interconnectedness, leverage, liquidity risk and maturity mismatch. The Office of Financial Research provides the FSOC data on BHC's and non-BHC's. It can also collect

information from government agencies such as the Federal Insurance Office. Once enough data has been collected, it is analysed to determine if/which of the six thresholds it exceeds:

    i) $50 billion or more in total consolidated assets. For hedge funds, this refers to Assets Under Management (AUM).

    ii) $30 billion or more in gross notional credit default swaps outstanding, where the nonbank financial company is the reference entity.

    iii) $3.5 billion or more of derivative liabilities.

    iv) $20 billion or more in total debt outstanding.

    v)   15 to 1 leverage ratio of total consolidated assets to total equity.

    vi)   10% short-term debt ratio of total debt outstanding with a maturity of less than 12 months to total consolidated assets.

For a nonbank to progress to the second Stage in the identification process, it must satisfy the size threshold in conjunction with any other threshold. This implies that for a hedge fund to be systemically important, it must be large. It then moves onto Stage 2.

2. **Stage 2**: the first review. Using information from the Office of Financial Research, the FSOC undertakes a comprehensive analysis of the company with respect to the six thresholds identified in Stage 1. Company information can also be obtained through public and regulatory sources, or documents voluntarily submitted by the company itself. If it is considered to pose a potential threat to financial stability in the event of a sharp decline in performance, it is moved onto Stage 3.

3. **Stage 3**: notification and direct information request. The FSOC notifies the company of its situation, and requests data around transactions and interactions with regulated banks (or subsidiaries of them), the risk management systems they have in place, as well as reports on their overall financial condition. Both quantitative and qualitative analysis is performed to

determine if the company will be subject to supervision by the Board of Governors and prudential standards.

In order to progress from Stage 1 to Stage 2, the size threshold must be met in addition to any other threshold. Though a range of funds may exist with over $50bn in AUM, the other conditions are more difficult to identify. Given the complex and dynamic nature of hedge fund trading, hedge funds may meet thresholds 2-6 however only intermittently. They can re-adjust positions when they exceed thresholds to avoid potential supervision. For example, the 15 to 1 cap on leverage ratios is a static measure and can be taken at a point in time. Meanwhile, hedge fund leverage is not static, and changes frequently to align with arising mispricing opportunities (Kruttli, Patton and Ramadorai 2014). The detection mechanism and method will only pick up hedge funds who consistently exceed these thresholds, making it relatively easy for them avoid supervision by only exceeding them for short periods.

If a hedge fund is passed through all three Stages, the FSOC can then decide if it will be subject to supervision by the Board of Governors of the Federal Reserve. This decision is based on a vote from council members (which includes the Secretary of the Treasury [who chairs the Council], the Chairman of the Federal Reserve and the Director of the Consumer Financial Protection Bureau among seven others), where at least two-thirds of members must concurrently agree on the company being systemically risky. In making the final conclusion, the Council considers the following:

i)   How levered the company is.

ii) The nature of its off-balance sheet exposures.

iii) The interconnectedness of the company with other large players in the financial services industry, including both banks and nonbank financial companies.

iv) How important the company is with respect to extending credit in the US.

v) The characteristics of the company's liabilities.

vi) Any other risk-related factors that the Council deems appropriate.

The FSOC recognizes that data from hedge funds is less accessible than other nonbank financial companies. It also acknowledges that it would not be appropriate to assess each of the companies identically, and so analyses them on a case-by-case circumstantial basis. The 2016 FSOC Annual Report suggested that the extensive use of leverage in the hedge fund industry required further analysis and oversight. It expressed that going forward, it will aim to strengthen engagement, analysis and monitoring, as well as data collection. To do this, it plans to create an interagency working group that will share and analyse relevant regulatory information to identify and assess potential risks to financial stability. It will perform the following functions (FSOC 2016):

1. Use regulatory and supervisory data to evaluate the use of leverage in combination with other factors—such as counterparty exposures, margining requirements, underlying assets, and trading strategies—for purposes of assessing potential risks to financial stability.

2. Assess the sufficiency and accuracy of existing data and information, including data reported on Form PF, for evaluating risks to financial stability, and consider how the existing data might be augmented to improve the ability to make such evaluations.

3. Consider potential enhancements to and the establishment of standards governing the current measurements of leverage, including risk-based measures of leverage.

The functionality of the FSOC remains a work in progress. It does not have an easy role in monitoring the shadow banking sector which offers so little transparency to regulators, but it is making consistent efforts and improvements to reduce financial instability in the US. One criticism I have for the method of monitoring is that it allows risk-taking *to the point* where it could become systemically risky. It

would fail to pick up sudden performance or liquidity problems, and the speed of detection is important if it is to prevent systemic crises.

It is often difficult to analyse the effects of structural changes as precise dates of implementation are unknown. Because the FSOC first came into effect on an easily identified date (July 21st 2010), this provides an opportunity to explicitly test its success in identifying, monitoring and regulating hedge funds with respect to systemic risk.

The formation of the FSOC as part of the Dodd-Frank Act was as one of two provisions that had implications for the hedge fund industry, and directly targets its implications for systemic risk. The other provision – the Volcker Rule – targets systemic risk indirectly, by reducing risks to the banking sector that may arise from the hedge fund sector, or vice versa.

2.6 The Volcker Rule

The Volcker Rule bans banks from investing in hedge funds. Its proposal faced much scrutiny from large US banks, as a series of successful lawsuits were filed in a bid to delay or change the regulation in fear of becoming less competitive globally. The rule prohibits banks from engaging in proprietary trading[4] (with some exceptions such as risk-mitigating hedging, underwriting activities and market-making activities), owning, acquiring or sponsoring hedge funds and private equity funds. The idea is to prevent banks from exposing themselves (as well as their clients) to high-risk trading strategies whose failure could trigger a capital shortage. It led to backlash from Wall Street banks, who lobbied

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[4] Proprietary trading refers to the buying and selling of securities or instruments on the banks own accounts rather than for its clients.

against the rule (CNBC 2016, Reuters 2011) until it went into full effect April 21st 2014. Full compliance with the ban on proprietary trading activities was first required by July 21st 2015, however on July 7th 2016 The Federal Reserve extended this to July 21, 2017 for legacy covered funds[5] and certain foreign funds. That the Volcker Rule was created means regulators identified that hedge funds and their performance and behaviour may have systemic implications through its interactions with the banking sector. The Dodd-Frank Act was designed to protect the financial system, largely held together by banks. It is thus in the best interest of regulators to protect the banking sector, as well as any other industry that may have a significant impact on it.

Despite the Volcker Rule's delayed enactment, there is evidence of large banks beginning to prepare for compliance before it was fully implemented. In 2010, Goldman Sachs sold its proprietary trading desk to private equity firm KRR (Fortune 2015). Bank of America Merrill Lynch also cut its proprietary trading unit in 2010, emphasizing it was not down to poor performance but rather was done in preparation for compliance with the Volcker Rule (New York Times 2010). Morgan Stanley also spun its trading division off into PDT Partners in 2012 (The Financial Times 2011). These precautionary steps suggest that the threat of future regulation may influence present behaviour. Given these empirical observations, I test if the threat of regulation can work as actual regulation by determining the effectiveness of the Volcker Rule from August 2010 – the time it was first proposed rather than April 2014 when it was fully enacted. The theoretical foundation for this idea lies in regulatory uncertainty.

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[5] Legacy covered funds refers to investments made before December 31, 2013.

2.7 Regulatory Uncertainty

Regulatory uncertainty refers to potential future policy changes that could significantly impact the day-to-day operations of a firm. The literature that explores this is sparse and is not limited to only regulatory uncertainty, but also economic, market or political uncertainty. While the context of the uncertainty is different, the theory underpinning each of these is much the same. Most literature around uncertainty in general is related to corporate finance and investment decisions. Bernanke (1983) and Bloom and Bond (2007) developed models to show that in periods of higher uncertainty, firms would delay investment. This is because uncertainty increases the real option value to invest, and so it is less costly to invest in the future rather than immediately. In a Knightian uncertainty context, a probability cannot be assigned to future events and thus cash flows, meaning no capacity to calculate NPV and thus the delay of investment. Julio and Yook (2012) examine the effect of political uncertainty on firm investment in the context of presidential elections where the outcome has a significant impact on policy and therefore the firm. They find firms reduce investment during election years by an average of 4.8%. Pástor and Veronesi (2013) develop an equilibrium model of political uncertainty that captures changes in government policiy to determine its effect on asset prices. After decomposing the equity risk premium into capital, impact and political shocks, they find that political shocks – such as an unexpected policy change – are significant, and that a "political risk premium" exists in stock returns. Government policy thus has a substantial effect on stock prices and therefore market performance. This evidence justifies the use of market returns in this study to capture the effects of a change in regulation, as policy changes the way a firm can operate and can thus impact its fundamentals.

The literature surrounding regulatory uncertainty is generally contained to environmental or energy laws, which have a major impact on the way firms operate, what and how much they can produce and their method of production with respect to emissions. Engau and Hoffman (2009) use survey data to

show that firms postpone decisions and create response strategies when they face regulatory uncertainty. Fan, Hobbs and Norman (2010) analyze firm investment choices under uncertainty around emission allowances, and find that risk-averse firms postpone investment decisions, while risk-neutral firms continue to invest. Similarly, Fabrizio (2012) found firms would invest less into new assets in states that had previously passed and repealed legislation to restructure the electricity industry. This again supports the idea that regulatory uncertainty induces delayed investment by firms. Lastly, Hoffman, Trautmann and Hamprecht (2009) investigate the investment decisions of German firms when there was uncertainty around the European Emission Trading Scheme, and find firms sometimes continue to invest despite uncertainty to try to secure competitive resources.

Although the literature summarised above is unrelated to financial regulation, the principles presented are transferrable. In the context of this study, regulatory uncertainty regarding the proposed ban on bank investment into hedge funds can create an incentive for banks to delay or withold investment to avoid future restructuring costs. Because the process for passing the Volcker Rule was dragged out by lobbying by banks and hedge funds (CNBC 2016, Reuters 2011), it allows for testing to see if financial regulatory uncertainty – or the threat of regulation – can induce voluntary compliance before the regulation is actually passed.

3.0 Hypothesis Development

This paper investigates the effectiveness of the Dodd-Frank Act in monitoring and regulating the hedge fund industry in the context of its effect on financial stability, and its interactions with the banking sector. The basic research question that arises from this is "*have US hedge funds been regulated more*

effectively since the 2010 Dodd-Frank Act?". To develop the testable hypotheses for this question, we must consider the nature and objective of each regulatory framework.

The Financial Stability Oversight Council aims to identify and prevent emerging threats from nonbank financial companies (such as hedge funds) to the stability of the US financial system. This can be interpreted alternatively as regulation designed to limit, restrict or eliminate the *direct* impact of hedge funds on systemic risk – the risk of the entire financial system collapsing. I call this effect the "direct systemic risk transmission mechanism". Threats to the system can arise through hedge funds if they are large, levered and highly interconnected with other institutions, and experience sudden, sharp drops in performance[6]. Using its three-step identification process, the FSOC would identify and place a hedge fund under supervision of the Board of Governors of the Federal Reserve if they conclude they it has the potential to be systemically risky. If this identification process has been efficient and successful, we would expect to observe a weaker relationship between hedge fund performance and systemic risk in the US since the 2010 Dodd-Frank Act and the inception of the FSOC. This leads to the development of the first hypothesis:

> *H_1: Hedge fund performance had a greater impact on changes in systemic risk in the US prior to the 2010 Dodd-Frank Act than it did after it.*

If results support H_1, they will indicate that the FSOC has successfully identified, monitored and regulated hedge funds that satisfied their identification criteria and could have systemic implications

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[6] Note that consistent poor performance is not necessarily systemically risky. Hedge funds struggle to grow in size if they do not perform as they fail to attract capital. Thus, the systemic risk arises from large hedge funds who experience abrupt declines in performance.

in the event of their collapse or failure. The direct systemic risk transmission mechanism would thus be significantly weaker than it would have been prior to the Dodd-Frank Act, providing half the answer to the research question – that hedge funds have been regulated more effectively since the Dodd-Frank Act with respect to systemic risk. It is important to note that we cannot directly attribute support for H_1 to regulation in the absence of true causality. The financial system experienced a significant overhaul because of the Dodd-Frank Act, and the increased investor risk aversion post GFC (Guiso, Sapienza and Zingales 2014) would also likely play a role. Support for H_1 would thus indicate regulation has had a role to play in reducing systemic threats from the hedge fund sector. If results do not support H_1, there is a fundamental problem with either the identification process, the monitoring process or the actual supervision imposed on hedge funds once they pass the identification process.

The second regulatory framework emerging from the Dodd-Frank Act to be tested in this paper is the Volcker Rule. Recall that the Volcker Rule prevents banks from investing in hedge funds to reduce or eradicate any intertwined risk exposure between the banking and hedge fund sectors. The introduction of this rule implies two things, the first being straightforward; that banks are systemically important institutions in the financial system. The second is that the interactions between banks and hedge funds can have systemic implications through their effect on the banking sector. This would imply hedge funds have an indirect effect on systemic risk, and their poor performance has adverse effects on the banking sector. I call this the "indirect systemic risk transmission mechanism" where hedge funds indirectly affect systemic risk through their effect on banks. If the Volcker Rule has been effective and working, I expect the following:

> H_2: *The US banking sector's performance exhibited stronger correlation with US hedge fund performance prior to the 2010 Dodd-Frank Act than it did after it.*

Success of the Volcker Rule would show a weaker relationship between US bank and hedge fund performance since August 2010. However, there is an issue in testing this hypothesis due to the true implementation date. It was first proposed as part of the Dodd-Frank Act to be introduced in July 2010, yet lobbying from Wall Street banks and hedge funds meant the rule did not come into effect until April 2014, with full compliance required by July 2015. To test if the relationship between banks and hedge funds has changed, a date must be identified where the Rule first began to influence the propensity for interactions between the two. When regulation is proposed and expected to be implemented at some future yet uncertain time, behaviour can begin to change in anticipation of future compliance costs that arise from restructuring. There is evidence of a response from banks before the Volcker Rule was passed. In 2010, Goldman Sachs sold its proprietary trading desk (Fortune 2015) and Bank of America Merrill Lynch cut its proprietary trading unit (New York Times 2010), while in 2012 Morgan Stanley spun off its trading division into PDT Partners (The Financial Times 2011). Each of these major restructurings were taken as precautionary steps in anticipation of the Volcker Rule, and provide the theoretical foundation for H_3:

> *H_3: The ex-ante threat of perfect regulation being implemented in the future can be more effective than the actual, ex-post and non-perfect regulation.*

I refer to this as the "regulation threat hypothesis", and it is conditional on regulation appearing theoretically perfect before it is employed. This is often the case with proposals, which are then lobbied against by institutions in the hope of achieving an outcome whereby either the perfect regulation does not influence their operating activities or performance significantly, or where there remain opportunities for regulatory arbitrage.

If H_1 and H_2 are both supported, there would be sufficient evidence to answer the research question that hedge funds have been better regulated sine the 2010 Dodd-Frank Act with a resounding "yes". The support for both hypotheses would also show that hedge funds directly influence systemic risk themselves (direct transmission mechanism), and indirectly through their connected activities with the banking sector (indirect transmission mechanism). Evidence showing only one of the transmission mechanisms is significant can shed some light to regulators about the angle at which regulation should target hedge funds from.

Results supporting H_3 would mean support for H_2, but would also open up a new strand of theory that relates to regulatory design[7]. If the ex-ante threat of regulation (which has little or no design costs and no ex post regret associated with regulatory failure) can achieve the same or better effect than immediately imposed regulation, regulators may have a new policy tool at their disposal – the threat of regulation alone. The foundation for this threat lies in uncertainty. If the market or institutions prone to the potential regulation cannot perfectly predict how it will be enforced, they are likely to anticipate the worst and as such, abstain from activities that may breach this regulation in future. Literature around regulation uncertainty shows evidence of this, as mentioned in Section 2.7 in the literature review.

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[7] Extensive research was done to try find financial or economic literature on regulatory threats. No such literature was found, however Maxwell, Lyon and Hackett 2000 showed that an increased threat of government regulation results in firms voluntarily reducing pollution emissions from toxic chemicals. Though this is in the context of environmental law, the theoretical foundations remain the same as those in this paper – that the threat of regulation can induce voluntary compliance to avoid future restructuring costs.

4.0 Data

To test the research question and associated hypotheses, I use NAV and return data for US hedge funds, market capitalisation and return data for US banks, and a unique dataset measuring total systemic risk (SRISK) in the US. A limitation of this research was the availability of hedge fund data with respect to AUM and leverage ratios. The Thomson Reuters DataStream database was used for hedge fund NAV's and returns, as access to hedge fund databases such as Hedge Fund Research and the Lipper TASS database was not available due to their high costs. While this may seem a limitation, it also mirrors the transparency problem regulators face when trying to monitor hedge funds.

4.1 Hedge Fund Data

US hedge fund data was accessed from Thomson Reuters DataStream. The constituent list "LUSHEDGE" provided by DataStream contained 2,391 US based hedge funds at the time of access. The list contains all US hedge funds who voluntarily submit their NAV and return data to DataStream, and so an inevitable self-selection bias exists. The large sample size mitigates this bias, as it contains both successful and unsuccessful funds that vary in size and adopt a range of different strategies – also making it representative of the US hedge fund industry. To clean the sample, the following funds were removed from the dataset:

    (i)   Funds without NAV or return data.

    (ii)   Funds that did not report their NAV in USD. This was done to avoid exchange rate effects when converting NAV to USD, as well as to avoid capturing risk factors that are not specific to the US financial system.

(iii)   Funds that had 6 months or less of return data. These funds were generally small spin-offs from other larger funds that would close soon after opening. Closure of these funds was generally not down to poor performance.

(iv)   Funds with an unknown key investment strategy.

(v)   Funds that had both an on-shore and off-shore operation using the same strategy. These would have the same and therefore very highly correlated returns; they were removed to avoid double counting.

(vi)   Funds with a fund of funds structure. These effectively double count returns, as their performance is dependent on the performance of other funds in the sample. By removing these, cross-correlation in returns is avoided.

This left a final sample size of 1,394 distinct, non-duplicated US hedge funds. A summary of the composition of fund strategies within the sample can be seen in Table 1.

Monthly Net Asset Values (NAV's) were used to calculate returns for each month. To ensure the accuracy of the calculations, they were matched against 'Hedge Funds Indexed Return' data from DataStream, which sets the funds' opening month NAV as 100 and indexes future NAV's against this.

The sample period covers January 15th 2004 to 15th January 2016; 6 years prior to the introduction of the Dodd-Frank Act and 6 years after. This is to ensure hedge fund performance is captured in two different regulatory environments; the years in the lead up to the introduction of the Dodd-Frank Act (implemented August 2010), and the post-Dodd-Frank Act period. The 15th day of each month is used as the base for return calculations to avoid any institutional effect on returns at the end of the month, when portfolio managers rebalance their portfolios in anticipation of quarterly bonuses.

Within the sample, both live and defunct funds are included to mitigate survivorship bias. It is important to include defunct fund performance, as it is in the very extremes of poor hedge fund performance when they fail that they are likely impact the banking sector and systemic risk. The sample is characterized by four types of fund lives:

a) Funds that were live prior to the sample period and became defunct within it (559).

b) Funds that became live, then defunct within the sample period (498).

c) Funds that became live during and were still live at the end of the sample period (197).

d) Funds that were live prior to, and were still live at the end of the sample period (140).

4.2 Core Bank Data

The constituent list 'LUSBANKS' provided by DataStream contained 32 commercial US banks at the time of download. It contains banks such as JP Morgan Chase & Co, Bank of America Merrill Lynch, US Bancorp, PNC Bank and Bank of New York Mellon – some the largest commercial US banks (US Federal Reserve 2016) – making it representative of the US commercial banking industry. Share prices and market capitalisation were downloaded for the sample period January 15th 2004 to January 15th 2016. The 15th day of each month is used for return calculations, as I posit that any interaction between the banking sector and hedge fund sector will have a contemporaneous effect on its counterparty. This is further explained in describing the model used in Section 6.2. Cleaning the sample involved removing two banks that were not based in the US and reported earnings in non-USD currency. A final sample of 30 commercial US banks is used, and are analysed in one aggregate bank portfolio. The portfolio construction method is expanded on in Section 5.2.

- Table 1 -

The composition of fund strategies within the sample. The first column indicates the strategy, and the second column categorises the strategy and provides a description of its investment style. Descriptions were drawn from Thomson Reuters Definitions Document (November, 2015), http://goo.gl/nCu8Pe.

Fund Strategy	Category; Description	# Funds
Convertible Arbitrage	**Relative Value;** Long position in a convertible security, short position in the underlying common stock.	23
Credit Focus	**Credit;** Invest in credit-structured vehicles to benefit in changes to credit quality, spreads or market liquidity.	77
Dedicated Short Bias	**Directional;** Consistently has 'net-short' exposure to the market.	6
Emerging Markets	**Directional;** Focus on investing in debt, equity or both of companies from emerging countries.	43
Equity Market Neutral	**Relative Value;** Aim to generate positive return in both up and down markets by having positions with zero total net exposure.	77
Event Driven	**Event;** Taking positions in various asset classes, seeking to profit from potential mispricing related to specific market events.	144
Fixed Income Arbitrage	**Relative Value;** Often highly leveraged, aims to profit by "playing the spread" between similar fixed income securities.	38
Global Macro	**Directional;** leveraged bets on anticipated price changes in extreme stock, interest rate, FX and commodity valuations.	39
Long Bias	**Directional;** similar to mutual funds, with the ability to trade a variety of instruments and the option to use leverage.	39
Long Short Equity	**Directional;** combines core long holdings of equities with short sales of stock or stock index options.	530
Managed Futures CTA's	**Directional;** aim to benefit from trends in any asset class by gaining exposure through futures, contracts and options.	235
Multi Strategies	**Mixed;** run several strategies, and can allocate capital dynamically between several traditional strategies.	100
Options Arbitrage	**Relative Value;** seek to capture the spread between similar options through inefficiencies in the market.	15
Other Hedge	**Mixed;** any fund that does not fit into the other categories.	28
		1,394

4.3 Systemic Risk - SRISK

For an institution to be systemically risky, it must be likely to face a capital shortfall precisely when the financial system is weak (Acharya, Engle and Richardson 2012). This is because when an individual institution faces a capital shortage, others can substitute for it and take over its intermediary activities in normal times. However, when the entire financial system is under stress, it is difficult for such substitution to occur. Acharya, Engle and Richardson (2012) construct an Expected Shortfall measure to measure total systemic risk (SRISK) [8] – the risk of the financial system collapsing. It captures the capital shortage faced by an institution when the financial system is weak. It is based on size, leverage and interconnectedness. I use the level of SRISK to calculate monthly changes (DSRISK) on the 15th of each month to align it with the hedge fund and core bank return data. This section briefly discusses construction and critiques of the measure.

First, the expected shortfall is calculated to determine the capital shortage faced by the financial system when a systemic event occurs:

$$ES_{m,t}(C) = E_{t-1}\left(r_{m,t} \mid r_{m,t} < C\right) = \sum_{i=1}^{N} w_{i,t} E_{t-1}\left(\left(r_{i,t} \mid \sum_{j=1}^{N} w_{j,t} r_{j,t} < C\right) \right)$$

(Eq. 1)

Where:

- *ES~m,t~* = expected shortfall, the expected market return conditional on it being less than C.

- *C* = threshold level that defines a systemic event (generally set to -40%).

- *r~m,t~* = return on the market at time *t*.

- *r~i,t~* = return of the institution at time *t*.

- *w~i,t~* = the institution's weight in the market index at time *t*.

- *E~t-1~* = conditional expectation on all information available at *t* - 1.

- *N* = total number of institutions.

The expected shortfall is defined by the expected return of the market, conditional on the fact its performance is below the threshold *C*. Since the market index is comprised of the value-weighted sum of returns, this expands to the second half of Eq. 1. The shortcoming of the expected shortfall measure is the ambiguity in setting the threshold that defines the systemic event. Further, using market returns restricts the model to listed institutions despite the fact that non-listed institutions can be systemically important. As such, SRISK does not include the systemic risk stemming from managed funds, hedge funds, unlisted insurance companies or unlisted banks. However, it does capture the systemic risk of listed institutions that is a result of their interactions with such counterparties. Lastly, using market may not reflect the fundamentals of the institution. While the model does use balance sheet data for debt levels in Eq. 4, it uses market prices to estimate the expected shortfall. This means that the expected shortfall represents the *market's expectation* of the shortfall, rather than what the *realized* shortfall would be in a market decline.

The contribution of each institution to the total shortfall is then measured using the Marginal Expected Shortfall (MES):

$$MES_{i,t}(C) = E_{t-1}\left(r_{i,t} \sum_{j=1}^{N} w_{j,t}r_{j,t} < C\right)$$

<div align="right">(Eq. 2)</div>

6-month market price changes are then estimated by duplicating a daily variation to determine an institution's' long run marginal expected shortfall (LRMES):

$$LRMES_{i,t} = -E_{t-1}\left(R_{i,t+6months}\big|R_{m,t+6months} < C\right)$$

$$\approx 1 - \exp(18 \times MES_{i,t}(2\%)$$

<div align="right">(Eq. 3)</div>

Where:

- $R_{i,\,t+6months}$ = exponential return of institution i in 6 months.

- $R_{m,\,t+6months}$ = exponential return of the market in 6 months.

Lastly, the balance sheet is used in conjunction with the LRMES to determine the SRISK of the institution:

$$SRISK_{i,t} = max\left[0; k\left(D_{i,t} + MV_{i,t}\right) - (1 - LRMES_{i,t})MV_{i,t}\right]$$

<div align="right">(Eq. 4)</div>

Where:

- $D_{i,t}$ = debt of the institution, taken from the balance sheet.

- $MV_{i,t}$ = market capitalization of institution i at time t.

    o $D_{i,t} + MV_{i,t}$ = proxy for total assets.

- k = capital ratio as required by regulation.

    o $k\,(D_{i,t} + MV_{i,t})$ = regulatory capital level.

- $(1 - LRMES_{i,t})\,MV_{i,t}$ = remaining capital in crisis event.

While I acknowledge the combination of market data and balance sheet data exposes the measure to approximations (Tavolaro and Visnovsky 2014), it includes variables that are relevant to systemic risk and can vary with the extent of interactions with hedge funds. Thus, the measure is sufficient for this study in measuring total systemic risk in the US.

5.0 Descriptive Analysis

5.1 Hedge Fund Analysis

For the purpose of the analysis, hedge funds were sorted into 10 size portfolios based on deciles, where portfolio 1 contains the smallest hedge funds and portfolio 10 contains the largest hedge funds. Portfolios are reformed each month, allowing a fund to move between portfolios if its NAV moves above or below the decile threshold. This is done for two reasons; the first is that the collapse of a larger hedge fund would more likely have more systemic implications. The second is that it allows for testing of the FSOC's regulatory success, given that the size criteria must be fulfilled in order for an institution to enter Stage 1 of the identification process.

I first analyse descriptive statistics of hedge fund returns for the pre and post Dodd-Frank Act (2010) periods, as well as for the full sample. Hedge funds can affect the banking sector and financial stability through poor performance, which can have a contagion effect other industries' performance and/or liquidity, as observed during the liquidity crisis following the near collapse of LTCM in 1998. Volatility in hedge fund returns can also play a role by generating uncertainty, panic from investors or again through a contagion effect on other assets and markets. The FSOC's restrictions on leverage ratios should theoretically reduce volatility in hedge fund performance by having a stabilising effect

on returns. If leverage caps are effective, I expect to observe reduced volatility in hedge fund returns post DFA as well as weaker performance, given that a major reason for the use of leverage is to generate returns that would otherwise be insufficient to investors (Ang, Gorovyy and van Inwegen 2011). I empirically observe both of these expectations in Table 2, which presents summary statistics for the mean monthly return and return volatility. This includes the entire sample across all size portfolios, as well as for the pre-Dodd-Frank Act period and the post-Dodd-Frank Act period.

- Table 2 -

The mean monthly return and return volatility for all size portfolios from 1 (smallest hedge funds) to 10 (largest hedge funds) for the entire sample period, the pre DFA period, and the post DFA period are presented above. Mean return is calculated as the average percentage change in NAV for the given portfolio across each sample and subsample period. To calculate the volatility, the standard deviation of hedge fund returns within each portfolio is calculated for every month. Then, the standard deviation of each monthly standard deviation value is calculated to get the portfolio return volatility for the particular sample period. "Change" refers to the improvement or worsening of returns and volatility, where + (-) indicates returns have improved (worsened) post-DFA relative to pre-DFA. For volatility, + (-) indicates volatility is improved (worsened), where an improvement is defined by a decrease in volatility post-DFA relative to pre-DFA.

Hedge Fund Portfolio	Mean Return				Return Volatility (σ)			
	Full Sample	Pre DFA	Post DFA	Change	Full Sample	Pre DFA	Post DFA	Change
1	-0.005	0.001	-0.014	(-)	0.014	0.016	0.010	(+)
2	0.001	0.010	-0.008	(-)	0.020	0.021	0.018	(+)
3	-0.007	-0.001	-0.014	(-)	0.013	0.016	0.010	(+)
4	-0.005	0.003	-0.016	(-)	0.014	0.014	0.012	(+)
5	-0.004	0.004	-0.013	(-)	0.014	0.014	0.014	(+)
6	-0.002	0.002	-0.006	(-)	0.017	0.019	0.010	(+)
7	0.000	0.008	-0.008	(-)	0.017	0.019	0.011	(+)
8	-0.001	-0.000	-0.002	(-)	0.018	0.020	0.013	(+)
9	-0.002	-0.001	-0.003	(-)	0.017	0.018	0.015	(+)
10	0.001	0.006	-0.003	(-)	0.017	0.018	0.014	(+)

The descriptive statistics indicate that since the new regulation was introduced, there has been a reduction and improvement in hedge fund return volatility across all size portfolios. This difference is likely to be driven by the high volatility in markets during the GFC before the Dodd-Frank Act, and

as such it is impossible to attribute causation of lower hedge fund volatility to regulation alone. Hedge fund returns are also lower in the post-DFA period. This can be attributed in-part to hedge fund behaviour around the time of the Lehman Brothers' collapse. Ang, Groovy and van Inwegen (2011) found that hedge funds deleveraged following the GFC, and that they are most likely to deleverage when their own returns are volatile in an attempt to reduce their volatility. This explains the observed decline in both performance and volatility following the DFA. Although summary statistics provide no reason to suggest causation, it is at least encouraging for regulators that the data exhibits these characteristics which coincide with formation of the FSOC, and the proposal of the Volcker Rule.

Hedge funds fail due to poor performance, which leads to high investor redemptions/outflows and eventually liquidation of the fund. While systemic risks are only likely to arise from the failure of large hedge funds, the simultaneous correlated default of many regardless of size can also have adverse effects on asset prices and liquidity. The observed deleveraging amid high return volatility within funds (Ang, Gorovyy and van Inwegen 2011) can also be a partial result of managers' expectations of a potential failure. If failure of the fund seems imminent, it has a legal obligation to repay its creditors. Figure 1 plots each year's corresponding attrition rate and mean monthly return for 2004-2015. A correlation of -0.506 suggests poor performance is linked with high attrition.

Figure 2 shows the regulation timeline and relevant attrition rates for hedge funds in each year of the sample period. The highest rate of attrition is 9.7% in 2015; nearly 1 in 10 hedge funds went defunct. This exceeds attrition rates even during the GFC, and interestingly coincides with the first full year of required compliance with the Volcker Rule which cuts bank investment into and sponsorship of hedge funds. The marginal decline in performance in 2015 indicated in Figure 1 appears to be too low to drive such a substantial increase in attrition. Similar declines in mean performance were accompanied by smaller marginal attrition rate increases in previous years. If the explanation for the high attrition

rate does not lie in performance, we must look to investor flows. Hedge fund inflows were at a 7-year high in 2014 at $111.4bn (eVestment Report 2016) before slumping in 2015 to $79.6bn (Preqin 2016). A near 30% decline in hedge fund flows would appear to indicate the Volcker Rule reduced the propensity of banks to interact with hedge funds. Again, the absence of causation makes it difficult to attribute such characteristics in the data to regulation. It seems as if the Volcker Rule was affecting bank behaviour from the time it was first proposed in August 2010 – well before its implementation in April 2014 – as attrition increased every year from 2010 onwards.

- Figure 1 -

Figure 1 plots the attrition rate and corresponding mean monthly return for the same period. The attrition rate is calculated as the number of hedge funds that went defunct in the year as a percentage of the total number of hedge funds that existed in the same year. Attrition and mean returns have a correlation of -0.506.
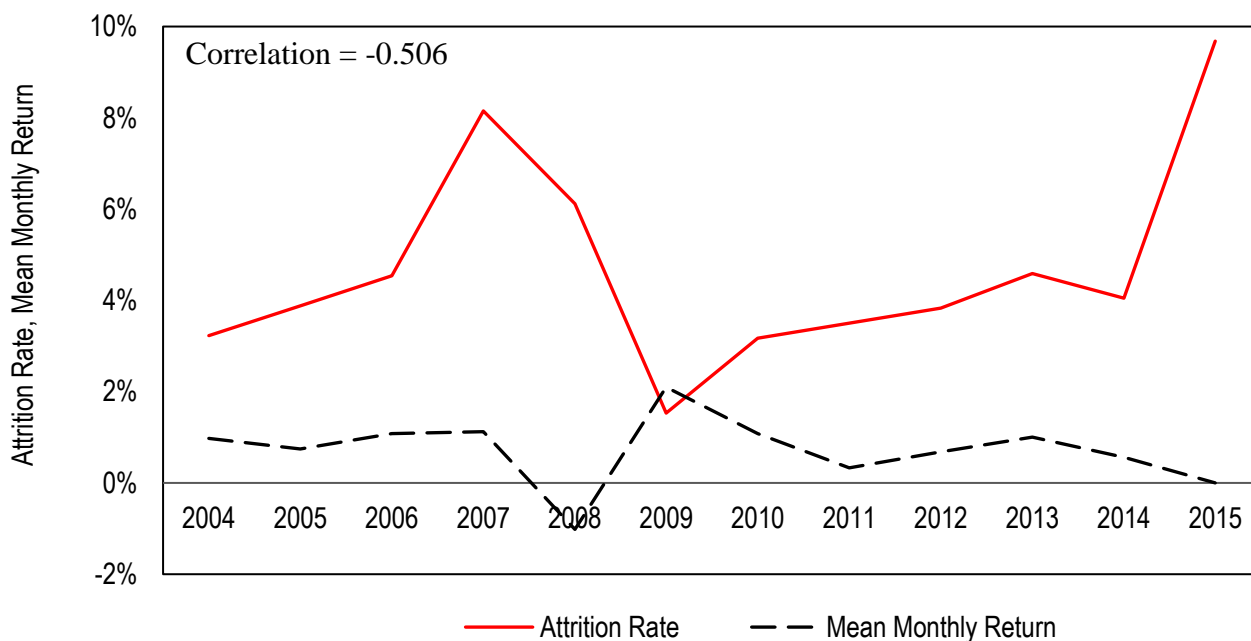
It is well documented that hedge funds have short lifespans and high attrition rates. Approximately 30% of new hedge funds do not survive longer than 36 months as a result of poor performance (Kat and Brooks 2002), and funds with two consecutive years of negative returns have a higher risk of shutting down (Brown, Goetzmann and Park 2001b).

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- Figure 2 -

Attrition rates are calculated for each year within the sample period, and are expressed as a percentage of the number of funds in that year.
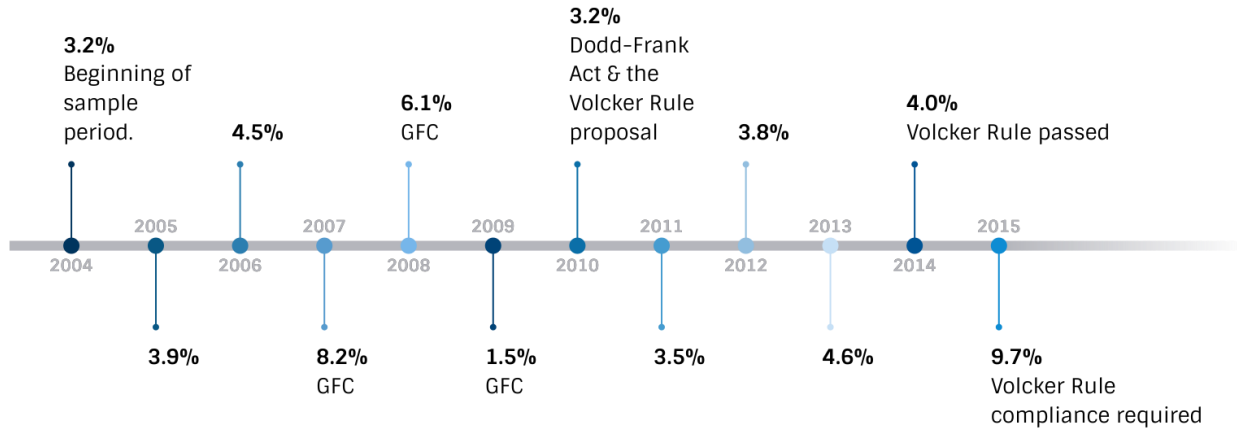
Howell (2004) found that the probability of a fund failing in its first year was 7.4%, increasing to 20.3% in the second. Attrition rates of 8.2% from 1994 to 2007, and 19.6% from 2007 to 2011 are also documented, and are attributed to the behaviour of managers who must cover previous year losses before getting paid a portion of next years' profits. This implies an incentive exists for managers to dissolve quickly and form new funds rather than recovering their previous losses (Bali, Brown and Caglayan 2014). The prevalence of this behaviour and resulting high attrition rates in the hedge fund industry pose a further problem for regulators. A mismatch exists in the average lifespan of a fund and the time-horizon around which its governing regulation is set. Policies are static and slow to respond the dynamic nature of the industry, characteristics that are present in the FSOC's three-stage process for identifying systemically risky hedge funds.

5.2 Bank Analysis

I analyse the core banking sector using an aggregate portfolio containing all 30 banks. Initially, banks were sorted into size portfolios based on terciles as well as quartiles. Results for the portfolio analysis

were providing misleading inferences. Since banks moved between size portfolios based on their market capitalization for a given month, there were extended periods when a portfolio would only contain between one to three banks. Despite the thresholds adjusting to capture size variations in each month, the marginal differences between two portfolio thresholds would be too small to make valid inferences with respect to different sized banks. This was not an issue with the hedge fund data due to the larger sample size (1,394). To ensure statistical validity, I analyse the banking sector's linkages with hedge funds using an aggregate portfolio containing all 30 banks. Table 3 shows summary statistics for the aggregate bank portfolio.

Mean monthly returns improved following the Dodd-Frank Act, however as in the case of hedge funds, the pre-DFA returns are lower due to effects of the GFC. Similarly, volatility declined following the DFA. Again, in the absence of established causality, new regulation has at least coincided with desirable characteristics in the banking sector's performance and volatility.

- Table 3 -

The mean monthly return and return volatility of the aggregate portfolio of US banks are presented for the entire sample, the pre-DFA period and the post-DFA period. Mean return is calculated as the average monthly return of all banks for the sample and subsample periods. The return volatility is calculated as the standard deviation of returns of all banks for the particular sample and subsample periods. "Change" refers to the improvement or worsening of returns and volatility, where + (-) indicates returns have improved (worsened) post-DFA relative to pre-DFA. For volatility, + (-) indicates volatility is improved (worsened), where an improvement is defined by a decrease in volatility post-DFA relative to pre-DFA.

	Mean Monthly Return				Return Volatility (σ)			
	Full Sample	Pre DFA	Post DFA	Change	Full Sample	Pre DFA	Post DFA	Change
Aggregate Portfolio	0.001	-0.001	0.006	(+)	0.066	0.076	0.051	(+)

5.3 Hedge Funds and the Banking Sector

Next, I look at the correlation between the hedge fund size portfolios' performance and the aggregate bank portfolio's performance. The Volcker Rule aims to cut – or at least reduce – ties and interactions between hedge funds and commercial banks by prohibiting investment, ownership or sponsorship of hedge funds by banks. Given this, the direction of the correlation is of less interest compared to its magnitude. If the Volcker Rule is effective and working I expect a decline in the absolute value of the correlation following the Dodd-Frank Act; that is that it moves towards 0. Table 4 shows the correlation of returns of all 10 hedge fund size portfolios with the aggregate bank portfolio containing all 30 banks. Panel A and B present correlations prior to and following the DFA respectively. Values that are bolded in Panel B indicate a "better" correlation post-DFA; post-DFA correlations that are smaller in absolute magnitude than they were pre-DFA. A "worse" correlation is defined as one that is larger in absolute magnitude post-DFA than it was pre-DFA and is not bolded in Panel B.

If the Volcker Rule – or the threat of it being implemented – is able to reduce co-movements in performance of the two, then it is effectively aiming to move the correlation to 0 regardless of whether it is positive or negative. It is possible that the threat of the Volcker Rule being passed would change the tendency for banks to interact with hedge funds. Credible threat of regulation forces an institution to plan well ahead of its enactment to avoid or reduce the future cost of adjustment. Consistent with the theme of this paper, I analyse the effects of the Volcker Rule from when it was first proposed and "threatened" to the banking sector – August 2014. Table 4 shows almost all hedge fund portfolios (except 6 and 9) exhibit weaker absolute correlation with the aggregate bank portfolio following the DFA. The scatterplot in Figure 3 allows for clear identification of the smaller spread of the coefficients since the DFA, clustering closer to zero. This suggests that the proposed introduction of the Volcker

Rule in 2010 began to limit bank and hedge fund interactions well before its implementation in April

2014. These descriptive results support the empirical analysis in Section 6.2.

- Table 4 -

This table shows the correlations between all 10 hedge fund size portfolios and the aggregate bank portfolio. Panel A presents correlations prior to the DFA and Panel B presents correlations following the DFA. A correlation bolded in Panel B indicates it has "improved", where its absolute value is lower for the post-DFA period relative to the pre-DFA period.

	Hedge Fund Size Portfolios									
	Panel A: Pre-Dodd-Frank Act									
	1	2	3	4	5	6	7	8	9	10
Aggregate Portfolio	-0.026	-0.207	0.057	0.104	0.063	-0.056	0.170	0.177	-0.056	-0.113
	Panel B: Post-Dodd-Frank Act									
Aggregate Portfolio	**0.003**	**-0.095**	**0.056**	**-0.036**	**0.014**	0.087	**0.098**	**-0.014**	0.081	**-0.022**

- Figure 3 -

A scatterplot of correlations between the aggregate bank portfolio and all 10 hedge fund portfolios for the pre DFA period. The y-axis indicates the values of the correlations, and the x-axis indicates the hedge fund size portfolio.
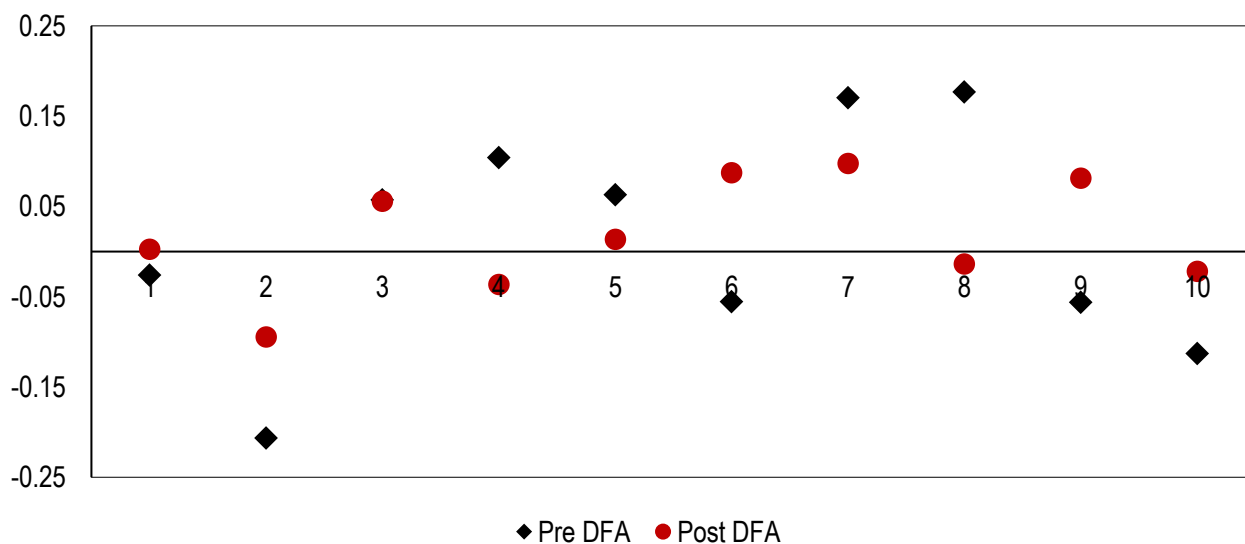
5.4 Hedge Funds and Systemic Risk

The Financial Stability Oversight Council aims to reduce systemic threats arising from hedge funds by setting leverage, credit default swap and derivative liability thresholds that when exceeded in conjunction with a size threshold, make it prone to regulatory oversight. The FSOC implies that for a hedge fund to have systemic implications through poor performance, it must be both large and significantly interconnected with the rest of the financial system. It is therefore expected the correlations between hedge fund performance and both SRISK (the level of systemic risk) and DSRISK (changes in the level of systemic risk) would be negative, and would be strongest for the largest size portfolios. Table 5 shows that the data exhibits this characteristic.

Panel A presents correlations for the pre-Dodd-Frank Act period. As expected, the largest hedge fund portfolios (7 through to 10) exhibit negative correlations which generally strengthen in absolute value for both SRISK and DSRISK moving toward the largest portfolio. This negative relationship justifies the size criteria set by the FSOC, as weaker performance from large hedge funds is correlated with higher levels and changes in SRISK. Panel B shows correlations for the post-Dodd-Frank Act period. Coefficients that are in bold in Panel B are deemed to have "improved", where an improvement is defined as a higher post-DFA correlation relative to its corresponding pre-DFA correlation. A weakening negative correlation (decreasing absolute value) implies hedge fund influence on systemic risk has declined. I define both "improving" and "worsening" differently in the relationship between hedge funds and banks, and hedge funds and SRISK/DSIRSK. The reason for this lies in the objective of different regulation. The FSOC would be most concerned with an explicitly negative relationship between financial instability (SRISK) and hedge fund performance, and tries to reduce the strength of this negative correlation. The Volcker Rule is targets the relationship between hedge funds and the

banking sector regardless of its direction, and tries to reduce the strength of their correlation whether

it be positive or negative.

- Table 5 -

Correlations between hedge fund portfolio returns and both SRISK (level) and DSRISK (changes) are presented below. Panel A shows correlations prior to the DFA, while Panel B shows correlations after the DFA. Correlations bolded in Panel B indicate an "improvement"; where the post-DFA correlation is higher than its corresponding pre-DFA correlation.

Hedge Fund Size Portfolios									
Panel A: Pre-Dodd-Frank Act									
1	2	3	4	5	6	7	8	9	10
DSRISK 0.130	0.133	-0.014	-0.132	-0.005	-0.104	-0.163	-0.086	-0.061	-0.142
SRISK 0.245	0.046	0.128	-0.038	-0.118	0.013	-0.069	-0.114	-0.107	-0.124
Panel B: Post-Dodd-Frank Act									
DSRISK 0.122	**0.147**	-0.129	**0.064**	**0.070**	**-0.045**	**-0.118**	**-0.027**	**-0.100**	**-0.065**
SRISK 0.165	**0.122**	0.082	**0.023**	**0.091**	**0.109**	**0.140**	**0.203**	-0.024	**0.056**

If a positive correlation has increased, it is less concerning for regulators as worse hedge fund

performance is associated with lower (both levels and changes) in systemic risk. Conversely however,

strong performance would be linked to higher levels and changes in SRISK. This makes sense

theoretically in the context of hedge fund leverage, as high leverage can be associated with strong

performance. Even if returns are high, systemic risk can be rising due to the risk of a potential default

and the interconnectedness of hedge funds with other financial and non-financial sectors. Portfolios 4

through to 10 all exhibit an improved relationship with both DSRISK and SRISK following the DFA;

an encouraging sign for the FSOC.

6.0 Empirical Testing and Results

I analyse the relationship between hedge funds and banks, and hedge funds and DSRISK separately. These analyses are separate as they effectively test two different provisions in the DFA as described in H_1 and H_2. Hedge funds can affect financial stability either through their interactions with the banking sector (Volcker Rule), or directly by collapsing and having implications for their counterparties (FSOC). This is important as it suggests that the exposure of the financial system to hedge funds can be through two distinct pathways. I use contemporaneous models for the reason that information has been so accessible to both hedge funds and banks over the past 20 years (which includes the sample period used) that any actions by one party in response to risks identified in the other party will be immediate to the extent that it is captured in monthly return data.

6.1 Model Development and Justification

A major difficulty for regulators in monitoring the financial system is the detection of systemic risks. Institutions or markets that are systemically risky (e.g. are in a bubble or on the verge of collapse) may not appear to be so until the negative consequences have unravelled and it is too late for regulators to intervene. Systemic risks may be seemingly non-existent in normal times, however can be extremely large in periods of financial crisis or turmoil. Using models that are conditional on the mean of a dependent variable would capture the average effect of the independent variable on the dependant variable. For regulators, this would mean failing to detect systemic risks on the basis that on average, the systemic risk does not exist. The relationship between a dependant and independent variable can vary in the extremes of the dependant variable's distribution, and standard Ordinary Least Squares regression models do not capture varying relationships for when the dependant variable is in the lowest or highest percentiles of its distribution. During these 'tail events' it may have a stronger, weaker or even opposite relationship with the independent variables. It is possible that given the frequent crises experienced by financial markets and the failure of regulators to prevent them, policy makers rely on

models based on conditional means. To put this in the context of my research, SRISK may have an insignificant relationship with hedge fund returns on average. The relationship may remain insignificant up until the 80th percentile in the SRISK distribution, and then becomes significantly stronger as it moves towards the 99th percentile.

I veer away from OLS regression techniques and instead adopt a quantile regression approach developed by Koenker and Basset (1978). A quantile regression models the relationship between the independent variable and conditional quantiles (percentiles) of the dependant variable, rather than the conditional mean as done in OLS. This offers a more comprehensive description of the relationship between the two, as although the relationship between the variables may is linear *in* the quantiles, it can show a non-linear relationship *across* quantiles of the dependant variable. The model appears linear in equation form, however can be non-linear when plotted (for example, see Figure 8 in Section 6.3). This technique also helps mitigate statistical issues common in hedge fund literature and data. Several advantages arise from modelling a relationship at different quantiles rather than at the mean. Firstly, least squares estimators in linear models are extremely sensitive to outliers, as they draw the mean away from the centre of a distribution leading to biased coefficients. Conversely, the quantile regression generates coefficients for every percentile meaning no single estimator is affected by outliers elsewhere along the distribution. Here, it succeeds in detecting systemic risk where an OLS would fail by picking up the outliers that would otherwise be discarded. The model is nonparametric, making no assumptions the distribution of the data, the distribution of errors or having constant variance (heteroskedasticity). This makes it robust to two statistical issues surrounding hedge fund performance literature. Jurek and Stafford (2015) argue against the use of simple linear models for hedge fund returns because they exhibit large kurtosis and skewness. Instead they use a replicating portfolio of put options to capture performance and hedge fund risks, however their model lies more in the field of asset pricing rather than attempting to model extremes in the hedge fund return

distribution. As such, the properties of the quantile regression model make it suitable for this research from two perspectives; the first being the detection of systemic risks which may seem non-existent on average, and the second being its statistical robustness to issues in hedge fund return data.

6.2 Contemporaneous Aggregate Bank Portfolio Analysis with Hedge Fund Size Portfolios: Testing the Volcker Rule

The first analysis looks at the relationship between the aggregate bank portfolio's returns and hedge size portfolio returns to determine the effectiveness of the Volcker Rule. It addresses H_2, that the US banking sector's performance exhibited stronger correlation with US hedge fund performance prior to the 2010 Dodd-Frank Act than it did after it. By using August 2010 as the date of the structural change for the Volcker Rule (despite not being fully implemented until April 2014), I also address H_3 – the "regulation threat hypothesis" where the ex-ante threat of perfect regulation being implemented in the future can be more effective than the actual, ex-post and non-perfect regulation.

I use a quantile regression model in this analysis for similar reasons described in Section 6.1. It is possible – and more likely probable – that hedge funds and banks do not exhibit particularly strong co-movements in performance day to day. They may be exposed to each other, however only in times of stress when performance of one industry might significantly affect performance in the other, or has market-wide liquidity implications if the institution is large enough (such as Lehman Brothers, or Long-Term Capital Management). Using quantile regressions allows more information of co-movements between the two to be extracted. Importantly, it models the varying relationship for extreme swings in bank performance where a prominent role for hedge funds would be most concerning for regulators. It can thus detect a relationship between hedge fund performance and bank performance that may not exist on average.

Regulators would unlikely be concerned by small fluctuations in bank returns correlated with hedge fund returns. Instead, they would be on high alert when bank and hedge fund returns co-move in periods of market stress, or if they co-move only when banks are performing in their extremes. This would indicate that the interaction between the two sectors may be damaging particularly when the financial system is at risk of collapse; in-line with Acharya *et al*'s (2010) definition of an institution being systemically risky if it is undercapitalized precisely when the rest of the system is undercapitalized. If regulators follow this (or a similar) definition of being "systemically risky" in their identification process and combine it with an analysis that focuses on conditional extremes rather than means such as a quantile regression model, policy might be better guided through earlier detection of systemic risk.

I use contemporaneous hedge fund and bank returns to analyse the relationship between the two. Today's US markets are integrated and efficient enough that information about news, market-wide movements or major shocks is available in real-time. Bank and hedge fund returns are both calculated as at the 15th of each month to allow for contemporaneous matching. To illustrate this point and offer a counterargument for using lagged models, I refer to the recent events surrounding Deutsche Bank's $14bn fine for its involvement in the selling of toxic mortgage-backed securities in the lead up to the GFC. Within days of the fine being announced by the US Department of Justice, several large and influential hedge funds pulled billions of dollars from Deutsche Bank in the form of excess cash and derivative positions (see Australian Financial Review 2016, Wall Street Journal 2016). Their response to emerging risks was almost instantaneous in the context of the monthly returns used in this study. New risks are quickly identified by either sector and they react quickly enough that the effects of their actions will be captured in monthly return data.

I estimate the quantile regression model in Eq. 5 for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of bank returns, where the returns of the bank portfolio are regressed on each hedge fund size portfolio's returns. Hedge fund returns from August 2010 onwards are interacted with a Volcker Rule (VR) dummy variable to capture the effect of structural changes that ensued through regulation.

$$Q_{R_t^b}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}VR + \varepsilon_t$$

(Eq. 5)

Where:

- R_t^b = returns of the aggregate bank portfolio at time t.

- $\tau = \tau^{\text{th}}$ quantile of R_t^b.

- $R_{i,t}^{hf}$ = a matrix containing all i hedge fund size portfolio returns at time t.

- $\beta_i(\tau)$ = a vector of coefficients for each hedge fund portfolio i in the matrix, conditional on the τth quantile of bank returns.

- $\gamma_i(\tau)$ = a vector of coefficients for the dummy assigned to the hedge fund portfolio i from the matrix, conditional on the τth quantile of bank returns.

- VR = Volcker Rule dummy, = 1 for all returns after August 2010 inclusive, 0 otherwise.

Figures 4 and 5 plot the pre (β_i) and post (γ_i) Volcker Rule quantile regression coefficients respectively. The x-axis indicates the hedge fund size portfolio, and the y-axis indicates the value of the coefficient (β_i for pre-VR, γ_i for post-VR). Note the distinction between bank quantiles and hedge fund size portfolios; the bank quantiles refer to percentiles in the distribution of bank returns, while hedge fund portfolios refer to the grouping of similar sized hedge funds irrespective of where their returns lie in the distribution of all hedge fund returns.

I draw your attention to box outlining the 75th, 90th and 95th quantiles of bank returns for hedge fund portfolio 10 in Figure 4. The pre Volcker Rule coefficients generally exhibit a relatively stable and weak relationship with most hedge fund portfolios across most bank return quantiles. However, the is very different for the largest hedge fund portfolio (10) and upper quantiles of bank returns. The 75th, 90th and 95th quantiles of bank returns were negatively associated with portfolio 10's returns.

- Figure 4 -

Coefficient estimates for β_i from Eq. 5: $Q_{R_t^b}\left(\tau|R_{i,t}^{hf}\right) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}VR + \varepsilon_t$, where β_i is the coefficient for hedge fund returns before the Volcker Rule. Each coefficient is conditional on the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of bank returns, indicated by the different shapes and colours of the markers. The y-axis represents the values of the coefficients, and the x-axis indicates the hedge fund size portfolio where 1 is the smallest and 10 is the largest.
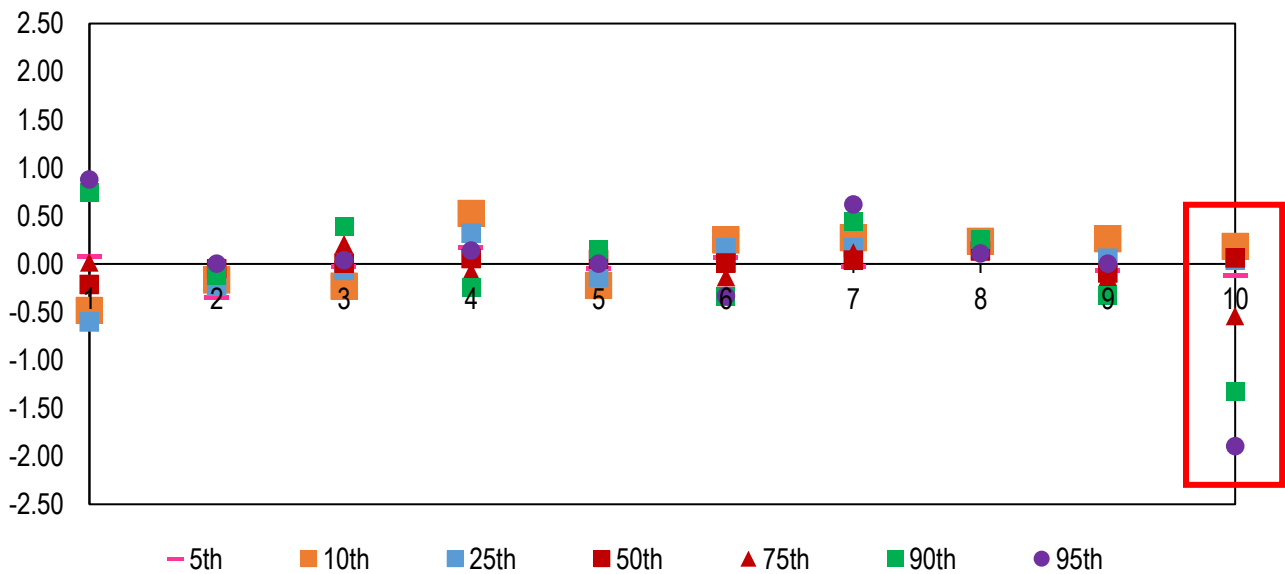
As we move up to the highest quantiles, the negative coefficients increase in absolute magnitude. Table 6 reports the coefficients and their t-statistics for hedge fund portfolio 10 at the 75th, 90th and 95th quantiles of bank returns. I do not report the coefficients and t-statistics (almost all of which are insignificant for all hedge fund portfolios at all bank return quantiles) for portfolios 1-9 for the reason that the quantile regression generates 154 coefficients for the model in Eq. 5, which is difficult to tabulate. Each of the seven bank return quantiles have 22 coefficients; 10 coefficients are generated

for hedge fund portfolio returns, 10 for hedge fund portfolio returns interacted with the Volcker Rule dummy, and one for the intercept and dummy respectively. As such, I present only the results for hedge fund portfolio 10, as no other portfolios showed significant coefficients. The results show that the largest hedge funds' performance was significantly and negatively associated with bank performance precisely when bank returns were in their extremes before the Volcker Rule was introduced.

- Table 6 -

Coefficient estimates for Eq. 5: $Q_{R_t^b}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}VR + \varepsilon_t$, where β_i is the coefficient for hedge fund returns before the Volcker Rule, γ_i is the coefficient for hedge fund returns after the Volcker Rule. Each coefficient is conditional on the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of bank returns. Values in parentheses beneath the coefficients represent their respective t-statistics *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

				Hedge Fund Size Portfolio 10			
				Bank Return Quantiles			
	5th	10th	25th	50th	75th	90th	95th
β_i	-0.415	-0.427	-0.359	-0.478	-0.968**	-1.259**	-2.169***
	(-0.940)	(-0.745)	(-1.209)	(-1.605)	(-2.151)	(-2.171)	(-3.815)
γ_i	-0.268	-0.234	0.113	0.772*	0.907	1.205*	2.596***
	(-0.560)	(-0.230)	(0.228)	(1.833)	(1.273)	(1.632)	(4.325)

The first question arising from the results in Figure 4 is why were regulators concerned with this negative relationship? If large hedge funds performed poorly when banks were doing well, why was this dangerous for the financial system? From a regulatory perspective, it makes it difficult to monitor and mitigate risks that have asymmetric effects on the two sectors. The suppression of a risk to banks by regulators could help improve bank performance, but could have a damaging effect on large hedge funds. It is in the best interest of regulators to keep banks and hedge funds simultaneously stable, as both are systemically important as seen by ramifications from the Lehman Brothers and LTCM collapse. The asymmetric movements in performance could also be the result of large hedge fund's

taking up large short positions around assets that banks were highly exposed to (e.g. mortgage-backed securities, credit default swaps, and collateralized debt obligations), or even around the bank stocks themselves in the lead up to the GFC. Such positions would explain the opposite movements in performance and the negative relationship in returns.

Figure 5 shows the coefficient plot for post Volcker Rule period. Coefficients for bank return quantiles 5, 10, 25 and 50 generally remain unchanged for portfolios 1-9. Encouragingly for regulators, the coefficients for quantiles 75, 90 and 95 are of similar magnitude and turn positive for the largest hedge fund portfolio post Volcker Rule. Note that the aggregate effect of the Volcker Rule is captured by the sum of the β_i and γ_i coefficients, which is close to zero for the 75th and 90th quantiles, and slightly positive for the 95th quantile. Why is this encouraging? For the 75th and 90th quantiles, the initial threat of the proposed Volcker Rule has supressed the relationship between hedge fund and bank performance. For the 95th quantile, the slightly positive relation post Volcker Rule is also encouraging. Assume large hedge funds are of the greatest systemic importance relative to smaller hedge funds. If both hedge funds and banks are exposed to risk factor X, but X has asymmetric effects on their respective performance, then any policy that inhibits X will be damaging to one industry yet beneficial for the other. While the Volcker Rule does not mitigate co-movements and sever the relationship totally, it succeeds in changing the relationship in a way that their risks can be simultaneously monitored by a single policy. Bali, Brown and Caglayan (2014) showed that hedge fund performance was better explained by economic uncertainty (measured through an index constructed of default spreads, term spreads and dividend yields among other macroeconomic factors including inflation and real GDP) than by traditional asset pricing risk factors such as the market, size, B/M or momentum. To the extent that banks are also exposed to macroeconomic risks, regulators can monitor such risk factors that are common to hedge funds and banks without setting policy that has confounding effects on each sector.

- Figure 5 -

Coefficient estimates for γ_i in Eq. 5: $Q_{R_t^b}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}VR + \varepsilon_t$, where γ_i is the coefficient for hedge fund returns after the Volcker Rule. Each coefficient is conditional on the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of bank returns. The y-axis represents the values of the coefficients, and the x-axis indicates the hedge fund size portfolio where 1 is the smallest and 10 is the largest.
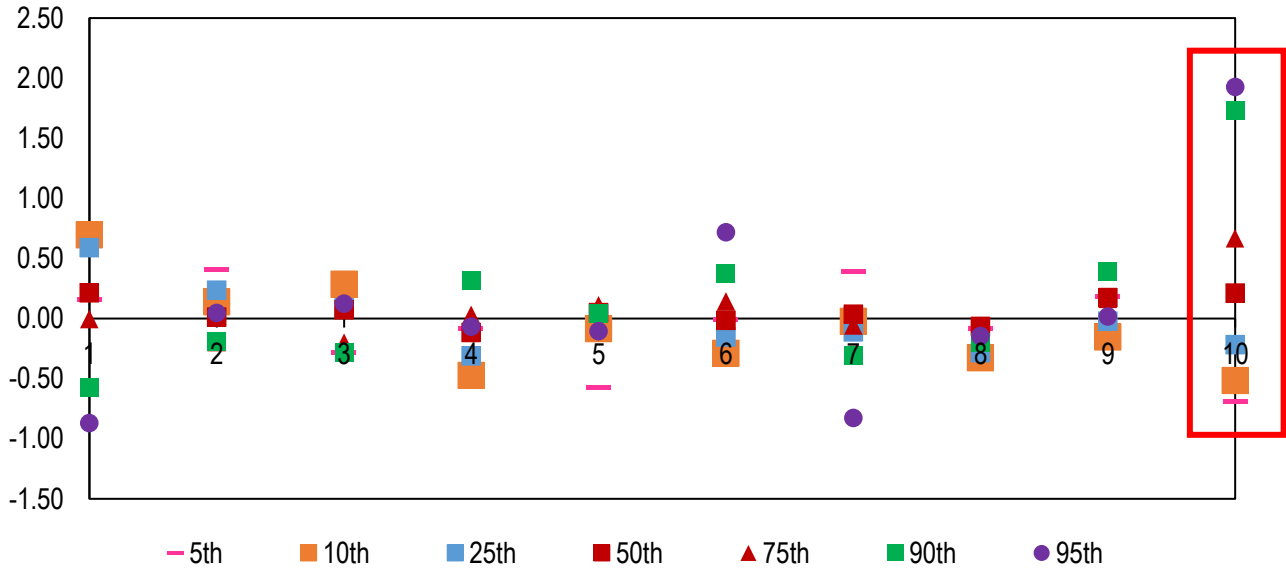
The results in Figure 5 and Table 6 indicate regulatory success of the Dodd-Frank Act's Volcker Rule, and offer support for H_2 – that the US banking sector's performance exhibited stronger correlation with US hedge fund performance prior to the 2010 Dodd-Frank Act than it did after it. The regulation not only succeeds in inhibiting this relationship, but also allows for easier monitoring of risks that previously had asymmetric effects on the banking and hedge fund industry when bank performance was in its extremes. The results hold when using August 2010 as the date of the structural change, providing support for the regulation threat hypothesis (H_3) where the ex-ante threat of perfect regulation being implemented in the future can be more effective than the actual, ex-post and non-perfect regulation. Support for both H_2 and H_3 yields interesting implications which regulators must consider.

To explain the phenomenon of the regulation threat hypothesis, I adopt to a modified version of the "bad news principle" proposed by Bernanke (1980). The bad news principle refers to the relationship between firm investment and uncertainty, positing that firms will delay investment amid high uncertainty because the value of the real option to invest increases as they wait for the uncertainty to subside. To contextualize this, consider the real option for a bank where it can invest in or sponsor a hedge fund, yet faces uncertainty as to when the Volcker Rule will require full compliance. We can assume that the proposed ban to prevent this interaction appears "perfect" in design; theoretically much regulation appears perfect when first proposed as loopholes are difficult to identify before knowing how it will be enforced[9]. If the banks continue to invest in or sponsor hedge funds prior to the full application of the Volcker Rule, they will face higher restructuring costs in the future when full compliance is required. As such, the real option value for banks to delay or withhold investment into hedge funds increases, because it reduces the future costs they face in adjusting to the structural change. This gives rise to the "regulation threat hypothesis". Making a law effective immediately may reach the desired behaviour change sooner, however it may not be the most efficient outcome. If the cost of immediate adjustment for the bank is high, the regulator may impose less costs on it by creating a credible threat of future regulation that will encourage adaptation while also allow time for restructuring, reducing the total cost of compliance and an overall more efficient outcome.

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[9] If regulatory arbitrage was identified well before its implementation, it is unlikely we would observe the extent of lobbying by both hedge funds or banks to change or delay the Volcker Rule, as well as the sell-off of proprietary trading units from Goldman Sachs, Bank of America Merrill Lynch, and Morgan Stanley. Loopholes are often discovered after the introduction of a new law, where institutions engage in regulatory arbitrage until the loophole is closed by regulators.

6.2.1 Granger-Causality Test: Bank and Hedge Fund Performance

The question that arises from results in Section 6.2 and Figures 4 and 5 is which industry drives the co-movements in performance? This is important for regulators as it reveals who is exposed to who. Since the quantile regression coefficients are significant only for the largest hedge fund portfolio, it appears the banking sector is mainly exposed to the hedge fund sector through its interactions with large hedge funds. I use a simple Granger Causality test to see if hedge fund portfolio 10's performance predicts bank performance or vice-versa. The test determines if future values of Y can be better predicted by the combination of both X and Y rather than by Y itself. That is, if bank returns can be better predicted using past bank and hedge fund returns than they can be predicted by past bank returns alone, then hedge fund performance is said to Granger-cause bank returns.

A limitation of this test – as with any test attempting to model causality – is that results cannot show true causality, as it is difficult to define causality in a statistical context (Granger 1980). A jointly causal variable that causes both bank returns and hedge fund returns may either not be included in the data or is unobservable, thus making it impossible to suggest one causes the other (Granger 1988). As such, the Granger-causality test reveals information about predictive causality, not true causality.

I first convert both the hedge fund returns and bank returns into a stationary time series. To run the test, I fit a bivariate VAR model to regress the dependant variable on itself and the independent variable, as well as p lags of the independent variable. I estimate the optimal number of lags using the

Akaike Information Criterion (AIC), based on the findings of Ivanov and Kilian (2005)[10]. The optimal number of lags is determined to be two ($p = 2$) for the pre VR returns, and one ($p = 1$) for the post VR returns. For robustness, I fit the model with lags $p = 1…4$. Lags beyond $p = 4$ are not economically reasonable given the speed of market efficiency in the US, where prices respond to information almost instantaneously (Busse and Green 2002) – well within the 4-month lags used. This is consistent with the argument for using contemporaneous models in Section 6.2 and 6.3.

Figure 6 and 7 show the respective pre and post Volcker Rule stationary time-series plots of the aggregate bank portfolio's returns and hedge fund portfolio 10's returns. In the lead up to the GFC and immediately after it (Figure 6), it seems that bank performance predicted hedge fund performance. Labels on the plot show that troughs in bank returns precede troughs in hedge fund returns (A precedes B), and peaks in bank returns precede peaks in hedge fund returns (C precedes D). This is unsurprising given that volatility in banks' stock market performance often has flow-on effects to different sectors as well as foreign stock markets. To test the apparent predictive power of bank returns observed in Figure 6 and 7, I run the test in both directions to see if hedge funds Granger-cause bank performance, or if banks Granger-cause hedge fund performance. The results of the Granger Causality test are reported in Table 7 for lags $p = 1…4$. The results associated with the optimal lags for the pre and post VR periods are presented in bold.

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[10]Ivanov and Kilian (2005) use simulations to show the Akaike Information Criterion produces the most accurate response estimates for VAR models that use monthly data. I use the AIC to determine the optimal lags used in the VAR as hedge fund and bank return data is monthly in this study.

- Figure 6 –

Stationary time-series plots of the aggregate bank portfolio and hedge fund portfolio 10's returns before the Volcker Rule. Labels A, B, C and D indicate bank performance troughs (A) predicting hedge fund performance troughs (B), and bank performance peaks (C) predicting hedge fund performance peaks (D).
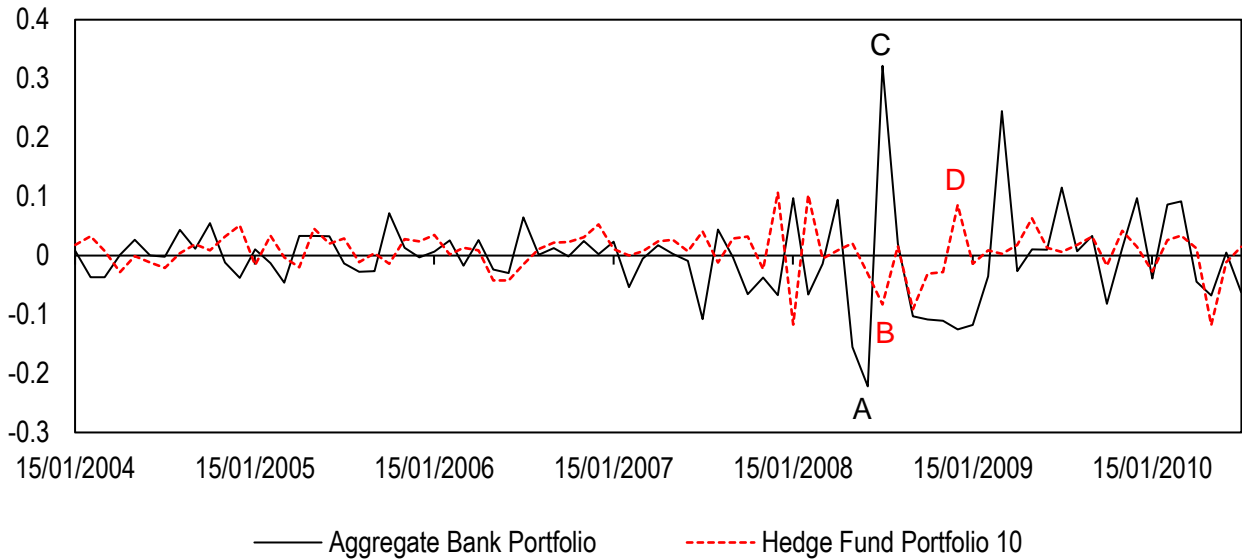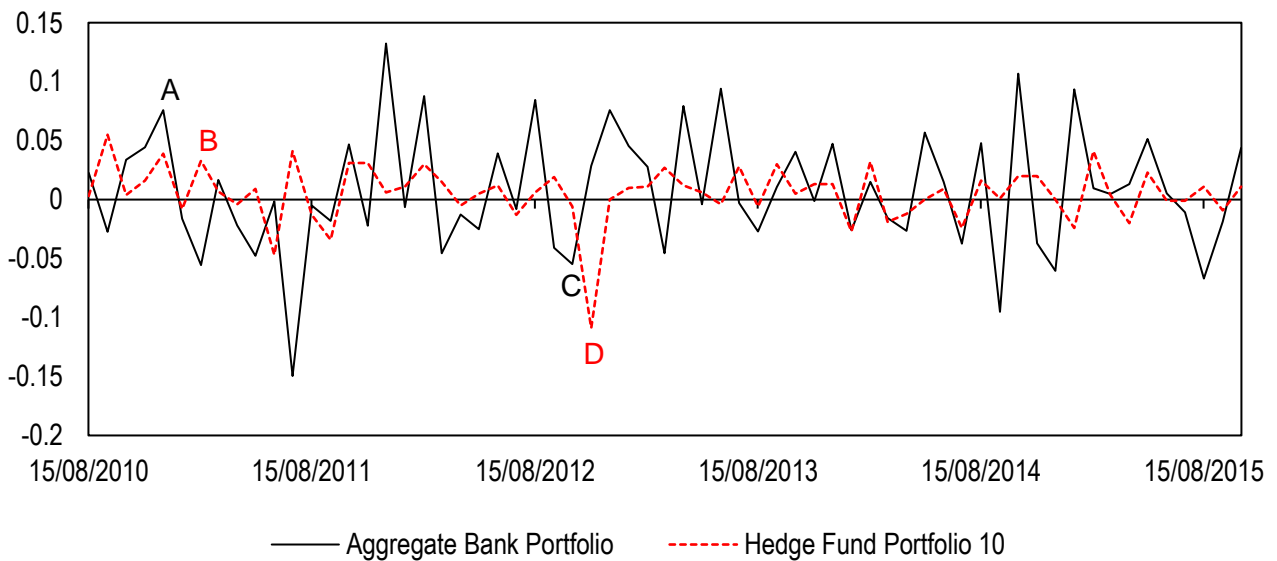

- Figure 7 -

Stationary time-series plots of the aggregate bank portfolio and hedge fund portfolio 10's returns after the Volcker Rule. Labels A, B, C and D indicate bank performance peaks (A) predicting hedge fund performance peaks (B), and bank performance troughs (C) predicting hedge fund performance troughs (D).

- Table 7 -

Results from the Granger Causality test are shown below. p indicates the number of lags in the fitted VAR model. Bolded values indicate the optimal number of lags for the pre ($p = 2$) and post ($p = 1$) Volcker Rule data. Values in columns 2-5 represent the F-statistics for the respective null hypothesis, and the values below them in parentheses represent their p-values. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

	H0: hedge fund portfolio 10 returns do not cause bank returns		H0: Bank returns do not cause hedge fund portfolio 10 returns	
	Pre VR	Post VR	Pre VR	Post VR
$p = 1$	0.025	**0.332**	6.498**	**5.151****
	(0.875)	**(0.566)**	(0.012)	**(0.025)**
$p = 2$	**0.563**	0.354	**3.324****	5.148***
	(0.571)	(0.703)	**(0.039)**	(0.007)
$p = 3$	1.097	0.380	2.249*	3.873**
	(0.353)	(0.768)	(0.085)	(0.011)
$p = 4$	1.315	0.415	1.863	2.891**
	(0.268)	(0.797)	(0.121)	(0.023)

Results in the table are clear and confirm the trends visually identified in Figures 6 and 7; that bank performance Granger-causes hedge fund performance for hedge funds in the top size decile. When using 1-month, 2-month and 3-month lags, the p-values reject the null hypothesis that bank returns do not cause portfolio 10's returns for both pre and post VR subsample periods. Their significance decreases when using 4-month (or more, unreported) lags pre VR; consistent with economic expectations and market efficiency. The encouraging sign for regulators is that for $p = 1$, the F-statistic has marginally declined indicating banks have a weaker causative relationship on hedge fund performance. It implies that the Volcker Rule has at least been slightly effective in limiting the interaction between banks and hedge funds, although has not yet achieved its desired effect of no interactions. It may be unrealistic to try restrict two large components of the financial services industry from engaging with each other completely given the wide integration of capital markets both domestically in the US and internationally. Nonetheless, the Granger Causality test results work as further support for H_2 and the indirect systemic risk transmission mechanism, showing there is an

innate relationship between the banking and hedge fund sectors that must be monitored to improve financial stability.

6.3 Contemporaneous DSRISK Analysis with Hedge Fund Size Portfolios: Testing Success of the FSOC

To test H_1 – that hedge fund performance had a greater impact on changes in systemic risk in the US prior to the 2010 Dodd-Frank Act than it did after it – and the direct transmission mechanism, I use quantile regressions to model the relationship between hedge fund returns and quantiles of DSRISK. The reason for using quantile regressions here is two-fold; first, since a standard Ordinary Least Squares (OLS) would model the relationship between hedge fund returns and the conditional *mean* of DSRISK, information is lost about how this relationship changes in periods of financial market and economic downturns and upturns when DSRISK is particularly high or low. Secondly and subsequently, regulators would react to large changes in SRISK rather than mean changes caused or correlated with hedge fund performance. To assess regulatory success, it is imperative to determine if hedge fund performance is no longer associated with large changes in SRISK rather than mean changes. Contemporaneous values of DSRISK and hedge fund returns are used for the same reasoning described in Section 6.2, where the assumption is that information flows are acted on quickly enough that their consequences are captured within one month of return data.

I estimate the following model using contemporaneous changes in SRISK (DSRISK) and hedge fund portfolio returns, where all hedge fund size portfolios are included:

$$Q_{DSRISK_t}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}DFA + \varepsilon_t$$

<div align="right">(Eq. 6)</div>

Where:

- $DRISK_t$ = the percentage change in SRISK at time t.

- $\tau = \tau^{th}$ quantile of $DRISK_t$.

- $\beta_i(\tau)$ = a vector of coefficients for each hedge fund portfolio i in the matrix of hedge fund size portfolio returns, conditional on the τth quantile of DSRISK.

- $R_{i,t}^{hf}$ = a matrix containing all i hedge fund size portfolio returns at time t.

- $\gamma_i(\tau)$ = a vector of coefficients for the dummy assigned to hedge fund portfolio i from the matrix, conditional on the τth quantile of DSRISK.

- DFA = Dodd-Frank Act dummy, = 1 for all returns after August 2010 inclusive, = 0 otherwise.

Since US regulators introduced laws around hedge funds to reduce their risk of increasing financial instability, it is implicitly implied that a negative relationship existed between hedge fund performance and DSRSIK prior to the Dodd-Frank Act and during the GFC (that is, weaker hedge fund performance would lead to greater upward changes in SRISK). If hedge funds are to be considered systemically risky in the context of Acharya *et al's* (2010) definition where they are undercapitalized when the rest of the system is undercapitalized, the relationship between hedge fund performance and systemic risk should be strongest in the upper quantiles of DSRISK. Thus, if the FSOC has been effective in reducing or weakening the effect of hedge fund performance on DSRISK, the coefficient related to hedge fund returns should exhibit one of the properties below, where τ refers to 75th, 90th and 95th quantiles of DSRISK (note that the comparison of the beta and gamma coefficients is for the same quantile):

$$\beta_i(\tau) < 0, \qquad \gamma_i(\tau) > 0$$

i) The coefficient was negative before the DFA (β_i) and became positive after the DFA (γ_i). This would show that rather than weak hedge fund performance being negatively associated with SRISK, it would be positively associated – a desirable effect for the FSOC and an indicator of successful monitoring of hedge funds.

$$\beta_i(\tau) < 0, \qquad \beta_i(\tau) < \gamma_i(\tau) < 0$$

ii) It was negative before the DFA, and became weaker but not positive after the DFA (i.e. lower in absolute magnitude). This would indicate successful monitoring of hedge funds, although not to the extent that is desired by the FSOC.

$$\beta_i(\tau) > 0, \qquad \beta_i(\tau) < \gamma_i(\tau)$$

iii) It was positive before the DFA, remained positive and became stronger after the DFA. Poor hedge fund performance would not create systemic risks. The converse – that strong performance is associated with higher DSRISK – is explained by high performance being driven by leverage (Ang, Gorovyy and van Inwegen 2011); SRISK may be rising due to the systemic implications of a highly levered hedge fund failing. I elaborate on this in the discussion of results later in this section.

Table 8 shows the coefficient estimates from Eq. 6 for each portfolio's returns for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of DSRISK. Panel A and Panel B contain the coefficients for the pre (β_i) and post (γ_i) DFA periods respectively. Coefficients presented in bold in Panel B are considered to have "improved", fulfilling one of the three criteria mentioned. Coefficients that did not satisfy one of the three criteria are deemed to have "worsened". The coefficient for most decile portfolios improved following the Dodd-Frank Act; most consistently for portfolio's 2 to 8. Improvements in

the coefficient are most consistent for the 90th and 95th quantiles of DSRISK on the right hand side of the table.

- Table 8 –

Coefficient estimates for the model $Q_{DSRISK_t}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}DFA + \varepsilon_t$, where β_i is the pre-DFA coefficient in Panel A, and γ_i is the post-DFA coefficient in Panel B. Each coefficient is conditional on the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of DSRISK. Values that are in bold indicate the coefficient "improved" following the DFA, where an improvement is defined by a change in coefficient from negative to positive, the weakening of a negative coefficient, or the strengthening of a positive coefficient. "Worsening" coefficients have not been bolded and do not exhibit any of the three characteristics described.

	Panel A: Pre-Dodd-Frank Act						
	DSRISK Quantiles						
Term	5th	10th	25th	50th	75th	90th	95th
β_1	0.237	0.476	0.710	0.470	0.345	0.629	-0.284
β_2	-0.361	-0.186	-0.182	-0.140	-0.067	-0.096	-0.392
β_3	0.346	0.073	-0.132	-0.137	0.064	0.139	0.101
β_4	-0.208	-0.316	-0.496	-0.392	-0.708	0.084	-0.495
β_5	0.145	0.169	-0.129	-0.176	-0.328	-0.599	-1.482
β_6	-0.457	-0.292	-0.324	-0.240	-0.436	-0.755	-1.365
β_7	0.119	-0.031	-0.120	0.012	-0.505	-0.826	-1.622
β_8	-0.235	-0.157	-0.011	-0.129	-0.376	-0.121	-1.785
β_9	-0.270	-0.176	-0.173	0.129	-0.307	-0.243	-0.604
β_{10}	-0.479	-0.289	-0.363	-0.353	0.514	1.313	2.713
	Panel B: Post-Dodd-Frank Act						
γ_1	**0.595**	-0.723	-0.533	0.273	0.095	-0.425	**0.750**
γ_2	**1.572**	**0.502**	**0.322**	**0.311**	**0.482**	**0.384**	**0.093**
γ_3	0.131	**0.463**	**0.239**	**0.116**	**0.070**	-0.129	-0.935
γ_4	**0.630**	**0.765**	**0.726**	**0.684**	**1.342**	**0.772**	**0.854**
γ_5	**0.547**	**0.464**	**0.644**	**0.466**	**0.813**	**0.792**	**0.865**
γ_6	**0.458**	**0.156**	**0.487**	**0.291**	**0.215**	**0.437**	**0.254**
γ_7	0.050	-0.182	-0.299	-0.420	**0.564**	**0.502**	**-0.120**
γ_8	**0.836**	**0.090**	-0.333	**-0.062**	**0.723**	**0.455**	**0.864**
γ_9	**0.633**	-0.330	**-0.033**	0.048	-0.308	-0.513	-0.845
γ_{10}	**0.712**	-0.644	**-0.122**	**0.669**	-0.568	-2.208	-4.315

This holds for portfolio 1 through to 8, and indicates that the FSOC has – to some extent – successfully monitored the hedge fund industry, and supressed the risks to financial stability that arise from it. However, it is important to note that the FSOC is unlikely be specifically targeting funds in these portfolios; their process for identifying systemically risky institutions involves the exceedance of a $50bn AUM size threshold. Hedge funds targeted by the FSOC would fall in portfolio 10 – the largest hedge fund portfolio. As such, portfolio 10 γ coefficients for the 90th and 95th quantiles (not bolded) of DSRISK are problematic for the FSOC. Their coefficients strengthen in Panel B, becoming more negative as we move to higher DSRISK quantiles.

Table 9 presents the t-statistics for hedge fund portfolio 10's coefficients both before and after the Dodd-Frank Act. As done for the bank portfolio analysis, I leave coefficients (most of which are insignificant) for portfolios 1-9 unreported due to the difficulty of tabulating 150+ values. While all but one of the coefficients are insignificant in Table 9, this is a strong indicator of the advantages in using quantile regressions for systemic risk analysis. The results show that poor performance from large hedge funds post DFA only has systemic implications when changes in SRISK are in their 95th quantile. Results show that large hedge funds are systemically risky exactly when DSRISK high, in line with Acharya *et al* (2010)'s definition of a systemically risky institution; one that has the propensity to be undercapitalized precisely when the rest of the financial system is undercapitalized. Again, note that the aggregate effect of the Dodd-Frank Act is the sum of the β_i and γ_i coefficients. The aggregate effect is similar to that in the bank results; systemic risks from large hedge funds have been supressed up to the 90th quantile, yet remain significant when changes in the level of systemic risk are at their highest.

- Table 9 –

Coefficient estimates for the model $Q_{DSRISK_t}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}DFA + \varepsilon_t$ for hedge fund portfolio 10, where β_{10} is the pre-DFA coefficient and γ_{10} is the post-DFA coefficient. Each coefficient is conditional on the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles of DSRISK, and bolded numbers indicate an "improvement" as defined in Table 8. Values in parentheses beneath the coefficients represent their respective t-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

	DSRISK Quantiles						
	5th	10th	25th	50th	75th	90th	95th
β_{10}	-0.479	-0.289	-0.363	-0.353	0.514	1.313	2.713
	(-0.949)	(-0.612)	(-1.326)	(-0.699)	(0.687)	(0.876)	(1.384)
γ_{10}	**0.712**	-0.644	**-0.122**	**0.669**	-0.568	-2.208	-4.315**
	(0.332)	(-0.444)	(-0.101)	(0.498)	(-0.415)	(-1.087)	(-1.959)

Considering that the FSOC uses size as its first criteria when assessing if an institution can threaten financial stability, it would be expected that they specifically target hedge funds in portfolio 10, and that the greatest improvement in the observed coefficients should then be for this portfolio. However, the empirical evidence shows that the opposite occurred, particularly for the 75th, 90th and 95th quantiles where the performance of large hedge funds exhibits a negative relationship with DSRISK. It is intuitive that the negative relation exists; when large hedge funds are performing poorly, systemic risk rises and as such, we expect high values for DSRISK. When hedge funds are performing well, there is no cause for concern and we expect low values for DSRISK. Although there is no danger in this, the FSOC aims to supress risks specifically arising when hedge fund returns experience sharp and sudden declines which can trigger systemic events.

To further analyse this, consider Figure 8 which shows the quantile regression plot for portfolio 10's pre-DFA (β_{10}, left-hand-side) and post-DFA (γ_{10}, right-hand-side) coefficients for all quantiles of DSRISK. Post-DFA coefficients are negative and increasing in magnitude as we move to higher DSRISK quantiles. Pre-DFA coefficients indicate the opposite relationship at the highest DSRISK

quantiles, where hedge fund performance and DSRISK were positively associated. I offer two explanations for this.

The first is that in the lead-up to the GFC large hedge funds were loaded up on mortgage backed securities, collateralized debt obligations and credit default swaps which were rising in value prior to the crash of the housing market. While this meant greater returns, they were unknowingly (depending on your view of their knowledge of the quality of these products) contributing to the increasing fragility of the financial system and thus increasing DSRISK.

The second is related to leverage. Ang, Gorovyy and van Inwegen (2011) showed that between 2005 and 2010, gross hedge fund leverage peaked right before the GFC, and was followed by significant deleveraging. Ben-David, Franzoni and Moussawi (2012) showed that during the GFC, hedge fund long positions exceeded their short positions, consistent with the observed deleveraging from Ang, Gorovyy and van Inwegen (2011). Both of these findings suggest leverage drove the trend in the pre-DFA plot of Figure 8, where coefficients increase as we move to higher DSRISK quantiles.

- Figure 8 -

The figures above show the pre (left) and post (right) Dodd-Frank Act quantile regression plots from Eq. 6 $Q_{DSRISK_t}(\tau|R_{i,t}^{hf}) = \alpha_i + \beta_i(\tau)R_{i,t}^{hf} + \gamma_i(\tau)R_{i,t}^{hf}DFA + \varepsilon_t$; the hedge fund return coefficients for portfolio 10. The y-axis indicates the coefficients, and the x-axis indicates the DSRISK quantiles. The dotted red line represents the OLS estimate of coefficients.
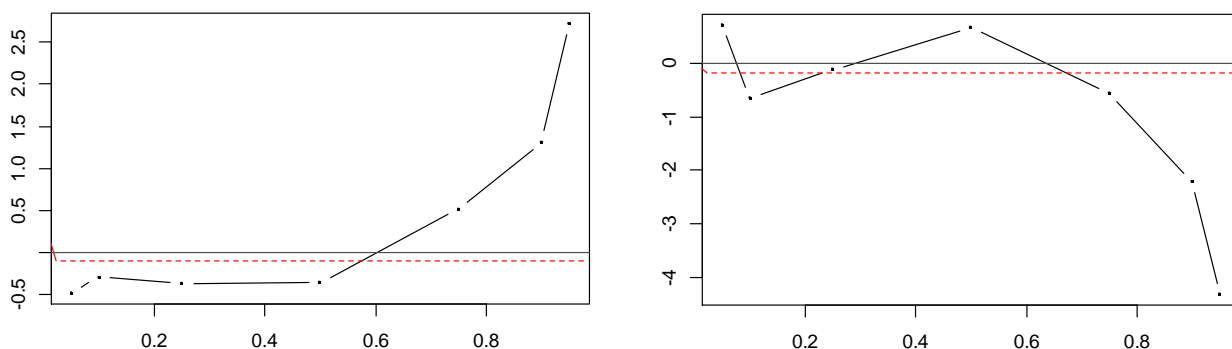
Note the dotted red lines in Figure 8 represent the coefficient estimates of an OLS model. The drawbacks of the OLS are clear; they fail to pick detect varying relationships in the extremes.

I hypothesize that a change in coefficient from negative to positive would imply a better relationship between DSRISK and hedge fund performance. For the largest hedge fund portfolio, the converse happens. This indicates that despite the FSOC's efforts to monitor large hedge funds, they are still able to engage in risky activities that can threaten financial stability. Whether this ability to evade stringent oversight is the result of poor work from the FSOC or the significant lobbying and political power of the hedge fund industry, more must be done to regulate these large and highly levered funds.

6.4 Hedge Fund Strategy Analysis

To test if the relationship between hedge fund performance and banks/DSRISK would vary depending on the strategy it uses, I analysed H_1 and H_2 using strategy portfolios rather than size portfolios. 14 portfolios were constructed based on their respective strategies from column 1 in Table 1. Hedge funds did not move between portfolios as they were grouped on strategy, not size. The same models were tested from Eq. 5 and Eq. 6 with respect to both the direct and indirect transmission mechanisms. No clear pattern or significance was observed in the results that would suggest regulation was working differently for funds deploying certain strategies. To ensure this was not a result of the portfolio strategies being too specific – such as "options arbitrage" – I formed four portfolios based on each strategy's "category" in column 2 of Table 1 (directional, relative value, event driven or mixed). No pattern or significance was observed in the results. Finally, I formed portfolios based on whether the strategy is directional (e.g. short only), semi-directional (e.g. long-short equity) and non-directional (e.g. relative arbitrage) as done by Bali *et al* (2014). Again, no pattern or significance is observed in the results. The failure to find results of interest in this section suggests there is no hedge fund strategy that is distinct from others with respect to the way it affects systemic risk or the banking sector.

7.0 Robustness

Several robustness checks and tests are undertaken throughout Section 6.0 to support validity of the results. Firstly, the hedge fund sample was cleaned to ensure that it did not double count funds by removing those that operate both an on-shore and off-shore fund using the same strategy, as well as removing funds-of-funds structures. Both live and defunct funds were included to mitigate survivorship bias, as it was important to include defunct funds to capture the risk they pose to the financial system. The sample is representative of the US hedge fund industry despite the selection bias, as it contains 1,394 funds with a well-diversified range of investment strategies.

The core bank sample is representative of the US commercial banking industry (US Federal Reserve 2016). Initially, banks were sorted into size portfolios based on terciles, then quartiles. Both of these portfolio construction methods did not produce statistically valid results because of the relatively small sample size, as banks could move between portfolios depending on their market capitalisation. At times, a portfolio would only contain one to three banks and so results from such a portfolio could be driven by an individual institution. Although the terciles and quartile thresholds adjust dynamically, the difference between the thresholds was at times too small to make statistically valid statements with regards to size. To mitigate this, I analysed the banks in an aggregate portfolio. These issues did not arise in the hedge fund data because of its much larger sample size.

Both tests of the FSOC and the Volcker Rule's effectiveness were done using quantile regressions for the reason that systemic threats may not exist on average, yet exist in the extremes of a risk factor's distribution. Models in Section 6.2 and 6.3 were also estimated using an Ordinary Least Squares regression, and no significant results were found. The success of the quantile regression in detecting

significant relationships in the upper quantiles of the bank and DSRISK distribution highlights the drawbacks of OLS. If the OLS model was used, I would have missed crucial information that would not only have implications for the results of this research, but also implications for regulators who may use similar models that based on conditional means. The use of quantile regressions is also more robust as it is nonparametric and makes no assumptions about their distribution, nor about the distribution of errors in the model. As such, it also allows for heteroskedastic errors by making no assumptions about their variance. Bootstrapped standard errors were used in the analysis, which also account for the non-normality of the data distribution.

To ensure the appropriate lags in the VAR model were used for the analysis, the optimal lags were estimated for the Granger-Causality test using the Akaike Information Criterion, rather than the Schwarz Information Criterion or the Hannan-Quinn Criterion. This is on the back of literature showing that for monthly data, the AIC produces the most accurate impulse response estimates (Ivanov and Kilian 2005). The optimal lags were found to be in line with economic expectations and market efficiency theories. For added robustness, the VAR model for the Granger-Causality test (which was done in both directions) was fitted with $p = 1…4$ lags. Results remained robust to all four lags. For any lags where $p > 4$, there exists no economic rationale for such a long response lag from the hedge fund industry to the bank industry or vice versa. When tested using lags $p = 5…10$, the F-statistics lost significance as the lag was increased, consistent with market efficiency theories.

Lastly, I construct portfolios based on hedge fund strategies to determine if the results from Section 6.2 and 6.3 are driven by a particular strategy that may create more systemic risks or be more harmful to the banking sector. Several portfolio construction methods were used and no significant results were found, nor was any trend or pattern in the data identified to suggest particular hedge fund strategies have a role in creating systemic risks or affecting the banking sector.

8.0 Conclusion

This paper highlights regulatory successes and shortcomings of the 2010 Dodd-Frank Act. Using quantile regressions, I show that systemic risks arising from the hedge fund sector may appear non-existent in normal times, however are large in periods when the financial system is under stress. The first and key contribution of this paper is that the introduction of the Financial Stability Oversight Council to monitor and regulate large, systemically risky hedge funds appears to have had limited success. Performance from large hedge funds has been negatively and significantly associated with DSRISK when DSRISK is in the 95th quantile of its distribution since the FSOC was introduced – this means that poor hedge fund performance is associated with large, positive changes in the level of systemic risk precisely when systemic risk is high. This qualifies large hedge funds as systemically important institutions based on Acharya *et al*'s (2010) definition of a systemically risky institution, and means that they affect systemic risk through the direct transmission mechanism. The reason I suggest for the FSOC's limited success is that it uses static measures to identify and monitor hedge funds it believes are a threat to financial stability, yet fails to consider that hedge funds are inherently dynamic in nature. Avoiding supervision from the FSOC and the Federal Reserve Board of Governors does not appear not difficult given the ease and speed at which a fund can adjust its positions and leverage.

Conversely to the shortcomings of the FSOC, the Volcker Rule has been successful in limiting the interactions of the banking sector and the hedge fund sector. A Granger Causality test confirms there is a link between the two, as bank performance Granger causes hedge fund performance. Using quantile regressions, I show that hedge fund performance and bank performance were significantly and negatively associated in the 75th, 90th and 95th quantiles prior to the Volcker Rule's first proposal in

2010. After the Volcker Rule was proposed, the relationship turned positive for the same upper quantiles, and only remained highly significant in the 95th quantile. The aggregate effect of the Volcker Rule indicates unwanted co-movements in performance between the two have successfully been mitigated. These results confirm two things; the first is that hedge funds affect systemic risk through the indirect transmission mechanism, by their performance being significantly associated with bank performance. The second is that a proposed total ban can be as effective as an imposed total ban.

This leads to the second contribution of this paper to both literature and regulators; support for the regulation threat hypothesis – that the ex-ante threat of perfect regulation being implemented in the future can be more effective than the actual, ex-post and non-perfect regulation. Due to the observed sell-off of banks' proprietary trading units following its announcement, I use the date of the Volcker Rule's initial proposal rather than the date of its full implementation to show that the threat of regulation can proxy for true regulation. When regulation appears perfect in theory upon initial proposal – such as the total ban on proprietary trading – it creates an incentive for its targets to voluntarily obey it before full compliance is required as it reduces future costs associated with adjusting to the structural change. Regulatory arbitrage thus cannot take place for regulation that does not yet exist.

I make two recommendations for future research based on this study. The first is to use leverage ratios to identify the specific hedge funds that would be, or have been monitored and regulated by the FSOC. This would allow a more explicit and direct test of how well the regulation has been inhibiting the effects of hedge fund performance on systemic risk. The second recommendation is to further explore the concept of regulatory threats using a range of regulatory proposals across different countries to see if the regulation threat hypothesis still holds.

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