CoVaR[*]

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Abstract

We define *CoVaR* as the Value-at-Risk (*VaR*) of financial institutions conditional on other institutions being under distress. The increase of *CoVaR* relative to *VaR* measures spillover risk among institutions. We estimate *CoVaR* using quantile regressions and document significant *CoVaR* increases among financial institutions. We identify six risk factors that allow institutions to offload tail risk, and show that such hedging reduces the wedge between *CoVaR* and *VaR*. We argue that financial institutions should report *CoVaR*s in addition to *VaR*s, and draw implications for risk management, regulation, and systemic risk. We define *Co-Expected Shortfall* as a sum of *CoVaR*s.

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1 Introduction

During times of financial crisis, losses tend to spread across financial institutions. For example, studies suggest that the 1987 equity market crash started by portfolio hedging of pension funds and lead to substantial losses of investment banks; that the 1998 crisis started with losses of hedge funds and spilled over to the trading floors of commercial and investment banks; and that the 2007/08 crisis spread from SIVs to commercial banks and on to hedge funds and investment banks (see Brady (1988), Rubin, Greenspan, Levitt, and Born (1999), and Brunnermeier (2008) for overviews of each of these scenarios). As a result of the spreading of losses, measured risk tends to spill across financial institutions.

The most common measure of risk used by financial institutions—the Value-at-Risk (*VaR*)—does not explicitly capture such risk spillovers. *VaR* is the dollar loss of an institution at a given percentage level, and is computed from the distribution of historical security returns (see Jorion (2006) for an overview of *VaR*). *VaR*s capture risk spillovers indirectly to the extent that institutions are exposed to common risk factors, but *VaR*s do not provide explicit information about the *co*-dependence of risk.

In this paper, we propose a measure of risk spillovers that is tightly linked to *VaR*. We call our risk measure *CoVaR*, where the "*Co*"stands for *co*movement, *co*ntagion or *co*nditional. We define *CoVaR* as the *VaR* conditional on other institutions' being in distress, more specifically conditional on other institutions' return being at their *VaR*-level. The percentage difference between the usual *VaR* and the *CoVaR* captures the degree to which a particular institution is exposed to risk spillovers from other sectors in times of stress. That is, while *VaR* captures the tail risk of financial institutions from a partial equilibrium point of view, *CoVaR* is a simple summary statistic capturing tail risk dependency – arguably a more important measure from a systemic risk point of view. To see this, consider two institutions, A and B, which report the same VaR, but while institution A's $CoVaR$=VaR, institution B's $CoVaR$ largely exceeds its VaR. In a world in which institutions A and B only report their VaRs, they appear to be equally risky. However, the high $CoVaR$ of institution B indicates that it is more exposed to system risk. Consequently, institution B should face stricter capital requirements and investors should require higher expected returns. In practice, we argue for a change of the regulatory framework that requires institutions to report their $CoVaR$s relative to the commercial bank universe, the hedge fund universe, and the investment banking universe, in addition to reporting their VaRs.

After defining $CoVaR$, we present empirical evidence that $CoVaR$s tend to be larger than VaRs across a broad set of financial institutions. For commercial banks, investment banks, and hedge fund styles, we document that average $CoVaR$s relative their respective benchmarks are significantly higher than the VaRs. For example, we estimate that $CoVaR$s of individual commercial banks relative to the commercial bank sector are on average 43% higher than individual VaRs. We find a $CoVaR$ percent increase of investment banks relative to the investment bank index of 24%, and a $CoVaR$ increase of individual hedge fund styles relative to the overall hedge fund index of 48%.

We also document significant $CoVaR$ increases across sectors. For example, we estimate a $CoVaR$ increase of commercial banks conditional on investment banks of 29% in the 1986-2008 sample, and of 43% in the 1926-2008 sample. In reverse, we find a $CoVaR$ increase of commercial banks conditional on investment banks of 45% for the 1986-2008, and of 37% in the 1926-2008 sample. In contrast, we do not find significant $CoVaR$ increases of commercial banks conditional on the hedge fund index, or of hedge fund styles conditional on the commercial bank index. Finding significant risk spillovers between hedge funds and investment banks, but not between hedge funds and commercial banks suggests that the tail risks of commercial banks and hedge funds are not tightly linked, but that the relation of investment bank risk and hedge fund risk is characterized by spillovers. We also define a *predictive CoVaR* that allows us to study delayed spillover effects and find that hedge fund sector stress predicts future stress for investment banks.

We then study the extent to which wedges between *CoVaR*s and *VaR*s are offloadable using six commonly traded risk factors. In particular, we are asking whether an institution that trades out of its exposure to tail risk explained by the six risk factors also reduces its *CoVaR* increase. We find that reductions in *VaR*s indeed tend to reduce *CoVaR* increases. Offloading strategies that reduce *VaR*s also tend to reduce *CoVaR*s, particularly across financial sectors. The risk factors that we identify do not allow trading out of all tail risk, but in principal, an institution can offload most tail risks. However, offloading tail risk is costly: offloading tends to reduce average returns. We thus find a risk-return tradeoff in trading out of risk, indicating that institutions generate returns by holding tail risk explained by our tail risk factors. The *CoVaR* measures the extent to which such tail risks are due to spillover risks.

We use quantile regressions to study risk spillovers. This method should appeal to a broad group of market participants for its simplicity and efficient use of data. For example, supervisors can make use of daily *P&L* and return data from regulated, supervised, and monitored institutions to assess the potential for spillover risk across institutions. Similarly, banks' risk managers can use intraday desk level *P&L*s to manage risk spillovers across trading desks. Fund-of-fund managers can use daily data from their constituent hedge funds to estimate risk spillovers across different hedge funds and use quantile factor loadings to off-load spillover risk.

Several authors have pointed out short-comings of the *VaR* and argued in favor of alternative risk measures. One of these measures is the expected short-fall (ES), which captures the expected loss conditional on being in the $\pi\%$ quantile. The beauty of our approach that it easily extend to other risk measures. In Section 4, we extend our analysis to the Co-Expected Shortfall (*Co-ES*). Just as *ES* is a sum of *VaR*s, *Co-ES* is a sum of *CoVaR*s. The advantage of *Co-ES* relative to *CoVaR* is that it provides less incentive to load on to tail risk below the percentile defined that defines the *VaR* or *CoVaR*. Reiterating, the economic arguments of this paper are readily translatable to expected shortfall.

Related Literature. Our *co-risk measures* can be interpreted in light of recent economic theories of financial sector amplification. While we do not test any particular theory, *CoVaR* is economically meaningful in economic settings where financing constraints of financial institutions are linked to risk. As measured risk increases, margin and capital requirements widen, forcing institutions to unwind. This tends to increase market risk, thus leading to further increases of measured risk. Brunnermeier and Pedersen (2007) propose a theory of margin spirals, where balance sheet constraints lead to risk spillovers among financial institutions. Adrian and Shin (2008) derive a micro foundation for the use of *VaR* by financial institutions, and analyze risk spillovers for financial systems of interlocked balance sheets. Kyle and Xiong (2001) provide a model of contagion among financial institutions where the interaction of risk spillovers and wealth effects leads to institutional contagion. Krishnamurthy (2008) reviews the literature.

Our paper can also be linked to several strands of literatures. First, our paper contributes to the growing literature that sheds light on the link between hedge funds and the risk of a systemic crisis. Boyson, Stahel, and Stulz (2006) document contagion across hedge fund styles using logit regressions. They do not find evidence of contagion between hedge fund returns and equity, fixed income and foreign exchange returns. In contrast, we show that our pricing factors explain the increase in comovement among hedge fund styles in times of stress. Chan, Getmansky, Haas, and Lo (2006) document an increase in correlation across hedge funds, especially prior to the LTCM crisis and after 2003. Adrian (2007) points out that the increase in correlation since 2003 is due to a reduction in volatility – a phenomenon that occurred across many financial assets – rather than an increase in covariance.

Second, our work relates to the large literature in international finance that focus on cross-country spillovers. For example, King and Wadhwani (1990) document an increase in correlation across stock markets during the 1987 crash, which in itself – as Forbes and Rigobon (2002) argue – is only evidence for interdependence but not contagion, since estimates of correlation tends to go up when volatility is high. Claessens and Forbes (2001) and the articles therein provide an overview. In contrast to these papers, our analysis focuses on volatility spillovers. The most common method to test for volatility spillover is to estimate GARCH processes, as e.g. in Hamao, Masulis, and Ng (1990) do for international stock market returns. While GARCH processes allow for time-variation in conditional volatility, they assume that extreme returns follow the same return distribution as the rest of returns. Hartman, Straetmans, and de Vries (2004) avoid this criticism by developing a contagion measure that focuses on extreme events. Building on extreme value theory, they estimate the expected number of market crashes given that at least one market crashes. However, extreme value theory works only best for very low quantiles (see Danielsson and de Vries (2000)). This motivates Engle and Manganelli (2004) to develop *CAViaR* that – like our approach – makes use of quantile regressions as initially proposed by Koenker and Bassett (1978) and Bassett and Koenker (1978). While Engle and Manganelli's *CAViaR* focus on the evolution of quantiles over time, we study risk spillover effects across financial institutions as measured by our *CoVaR*. More recently, Rossi and Harvey (2007) estimate time-varying quantiles and expectiles using a state space signal extraction algorithm. The machinery developed by Engle and Manganelli (2004) and Rossi and Harvey (2007) could be used to study the time variation of *CoVaR* in future work.

The remainder of paper is organized in five sections. In Section 2, we study the pairwise relationships between the returns to different financial intermediaries. In Section 3, we estimate a risk factor model for the hedge fund returns. We document that six commonly traded risk factors that explain average returns well, and that also explain the increase of *CoVaR* relative to unconditional VaR. We present robustness results in Section 4, and discuss implications for risk management and regulation in section 5. We draw conclusion in Section 6.

2 CoVaR

In this section, we first introduce our risk spillover measure *CoVaR*. We do this by means of quantile regressions – our method of estimating *CoVaR*.[1] We then describe the data and document that *CoVaR*s significantly exceeds the *VaR*s, meaning that the Values-at-Risk of commercial banks, investment banks, or hedge funds are significantly higher when other financial institution are in distress. Finally, we introduce a predictive CoVaR which helps to forecast an increase in the Value-at-Risk one month in advance.

[1] We estimate *CoVaR*s using quantile regressions as 1) it is computationally efficient, and 2) regression coefficients can be directly interpreted as portfolio weights. However, *CoVaR*s can be estimated via bootstrapping, time varying volatility models (such as stochastic volatility or GARCH models), or extreme value distributions, among others.

2.1 Definition of $CoVaR$

Recall that VaR_q^i is implicitly defined as the q quantile, i.e.

$$\Pr\left(R^i \geq VaR_q^i\right) = q,$$

which is typically a negative number. Practioners usually switch the sign, a sign convention we will not follow. It is also noteworthy that all our empirical results are expressed in percentage returns. These can be transformed into \$ amounts by multiplying by total assets.

Definition 1 *We denote the* CoVaR^{ij}*, the* VaR *of institution* i *conditional on the (unconditional) VaR of (index) return* j*. That is,* CoVaR^{ij} *is implicitly defined by q-qantile of the conditional probability distribution*

$$\Pr\left(R^i \geq \mathrm{CoVaR}_q^{ij} | R^j = \mathrm{VaR}_q^j\right) = q$$

Thus CoVaR_q^{ij} *gives the* VaR_q *of institution* i *conditional on the unconditional* VaR_q *of index* j*.*

We sometimes say that $CoVaR^{ij}$ is the VaR of style i conditional on index j being in distress.

Rather than reporting the $CoVaR$s directly, we report the percent increase relative to the unconditional VaRs

$$\frac{CoVaR^{ij} - VaR^i}{VaR^i} \cdot 100.$$

This has the advantage that it normalizes return data across different institutions / strategies with different unconditional VaRs.

As mentioned above, the *CoVaR* captures risk spillovers across different institutions. Ideally our "co-risk-measure" should also capture risk externalities that individual institutions do not fully take into account – an aspect that is at the center focus for the regulatory debate on how to change regulatory capital and margin requirements that take systemic risk externalities into account. In a recent speech, Federal Reserve Chairman Ben Bernanke put it in the following words:[2]

Under our current system of safety-and-soundness regulation, supervisors often focus on the financial conditions of individual institutions in isolation. An alternative approach, which has been called systemwide or macroprudential oversight, would broaden the mandate of regulators and supervisors to encompass consideration of potential systemic risks and weaknesses as well.

Another attractive feature of *CoVaR* is that it can be easily adopted for other "*co*risk-measure". One of them is the co-expected-shortfall, *Co-ES*, that we analyze in Section 4. Expected shortfall has a number of advantages relative to *VaR*, and can be calculated as a sum of *VaR*s. In the same manner, *Co-ES* can be calculated as an integral of *CoVaR*s.

2.2 Quantile Regression - one way to estimate *CoVaR*

The *CoVaR* measure can be computed in various of ways. Using quantile regressions is a particularly efficient way to estimate *CoVaR* but by no means the only one. Alternatively, *CoVaR* can be computed from models with time varying second moments, from measures of extreme events, or by bootstrapping past returns.

To see the attractiveness of quantile regressions, consider the prediction of quantile

[2] http://www.federalreserve.gov/newsevents/speech/bernanke20080822a.htm

regression of return i on index return j:

$$\hat{R}_q^i = \hat{\alpha}_q^{ij} + \hat{\beta}_q^{ij} R^j, \tag{1}$$

where $\hat{R}_q^i$ denotes the predicted value of excess return i for quantile q and R^j denotes the excess return of institution or portfolio j (a commercial bank, investment bank, or a hedge fund style index).[3] In principle, this regression could be extended to allow for nonlinearities by introducing higher order dependence of returns to style i as a function of returns to index j. From the definition of Value-at-risk, it follows directly that:

$$VaR_q^i | R^j = \hat{R}_q^i. \tag{2}$$

That is, the predicted value from the quantile regression of returns of style i on index j gives the Value-at-Risk conditional on R^j since the VaR given R^j is just the conditional quantile. Using a particular return realization $R^j = VaR^j$, yields our $CoVaR^{ij}$ measure.[4] More formally, within the quantile regression framework our $CoVaR$ measure is simply given by:

$$CoVaR_q^{ij} := VaR_q^i | VaR_q^j = \hat{\alpha}_q^{ij} + \hat{\beta}_q^{ij} VaR_q^j. \tag{3}$$

[3]Note that a median regression is the special case of a quantile regression where $q = 50\%$.We provide a short synopsis of quantile regressions in the context of linear factor models in the Appendix. Koenker (2005) provides a more detailed overview of many econometric issues.

While quantile regressions are regularly used in many applied fields of economics, their applications to financial economics are limited. Notable exceptions are econometric papers like Bassett and Chen (2001), Chernozhukov and Umantsev (2001), and Engle and Manganelli (2004) as well as the working papers by Barnes and Hughes (2002) and Ma and Pohlman (2005).

[4]It differs from the often used conditional VaR (CVaR), mean excess loss, expected/mean shortfall (ES), or tail VaR, which are all defined for a single strategy as $E\left[R^i | R^i \leq VaR^i\right]$.

2.3 Financial Institution Return Data

We focus on three groups of financial institutions in this paper: commercial banks, investment banks and hedge funds. We use the equity returns of the five commercial banks with the largest size of total assets in recent years (Bank of America, Citibank, JPMorgan Chase, Wachovia, and Wells Fargo), as well as the equity returns of five large investment banks (Bear Stearns, Goldman Sachs, Lehman Brothers, Merrill Lynch, and Morgan Stanley). The equity return data is from CRSP. We start our sample of individual banks in April 1986, as only two of the five investment banks were public prior to that date.

In order to analyze a longer time series of banking data, we also use the banking and security broker dealer portfolios from the 49 industry portfolios by Kenneth French.[5] These portfolios are constructed as value weighted averages from CRSP equity returns according to SIC codes, and are available since July 1926. Interestingly, the correlations between value weighted portfolios of the five commercial and five investment banks are, respectively, very highly correlated with the banking and security broker dealer industry factors (the correlation since April 1986 is over 90%).

In addition to commercial and investment banks, we also include hedge fund returns in our analysis. Hedge funds are private investment partnerships that are largely unregulated. Studying hedge funds is more challenging than the analysis of regulated financial institutions such as mutual funds, banks, or insurance companies, as only limited data on hedge funds is made available through regulatory filings. Consequently, most studies of hedge funds thus rely on self-reported return data.[6] We follow this

[5] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] A notable exception is a study by Brunnermeier and Nagel (2004) who use quarterly 13F filings to the SEC and show that hedge funds were riding the tech-bubble rather than acting as price-correcting force.

approach and use the hedge fund style indices by Credit Suisse/Tremont.

There are several papers that compare the self-reported hedge fund returns of different vendors (see e.g. Agarwal and Naik (2005)), and some research compares the return characteristics of hedge fund indices with the returns of individual funds (Malkiel and Saha (2005)). The literature also investigates biases such as survivorship bias (Brown, Goetzmann, and Ibbotson (1999) and Liang (2000)), termination and self-selection bias (Ackermann, McEnally, and Ravenscraft (1999)), backfilling bias, and illiquidity bias (Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004)). We take from this literature that hedge fund return indices do not constitute ideal sources of data, but that their study is useful, and the best that is available. In addition, there is some evidence that the Credit Suisse/Tremont indices appear to be the least affected by various biases (Malkiel and Saha (2005)).

[Table 1]

Summary statistics for the value weighted portfolio of the five commercial banks and the five investment banks for April 1986 to March 2008 as well as for the ten hedge fund styles for January 1994 - May 2008 are given in Table 1 (Panel A). The summary statistics for the longer time series of the bank and security broker dealer industry portfolios since July 1926 to March 2008 are given Panel B. The hedge fund style indices have been extensively described in the literature (see Agarwal and Naik (2005) for a survey), and characterizations can also be found on the Credit Suisse/Tremont website (www.hedgeindex.com).

The Sharpe ratio of the hedge fund index (0.26 monthly) is nearly twice as high as the Sharpe ratio of either commercial or investment banks (both 0.15 monthly). The average CAPM α's of the two banking sectors and hedge funds are of comparable magnitude (0.41, 0.43, and 0.38), but only the hedge fund α is statistically significant. Over the longer period since 1926, commercial banks have a slightly smaller α of 0.28 which is statistically significant, while security broker dealers have an α close to zero over the longer period. Sharpe ratios are of comparable magnitude for the longer and shorter samples of Panels A and B.

Commercial and investment banks exhibit negatively skewed standardized returns, while the skewness of hedge funds is closer to 0. In the longer sample, the banking and trading portfolios exhibit positive skewness. All institutions exhibit excess kurtosis relative to a normal distribution.

2.4 Estimates of *CoVaR*

For our baseline results, we report the value weighted average the *CoVaR* for the institutions within one group i (for example investment banks), conditional on the *VaR* of the overall index of other institutions j (or conditional on the own group i). For example, after quantile regressing each of five investments banks on the hedge fund index we obtain five CoVaR measures. We value-weight the five CoVaRs and report the weighted average.

Table 2 reports in the first column the unconditional VaRs which corresponds to the 5th percentile of the return distribution. Panel A gives the *VaRs* and *CoVaR*s for individual institutions, Panel B for the portfolios since 1926. In Panel A, the average unconditional 5%-*VaR* is −12.23% for commercial banks (since 1986), −13.69 for investment banks (since 1986), and −2.40% for the ten hedge fund styles (since 1994). The unconditional *VaR* in the longer data set is −10.13 for the commercial banks, and −11.83 for the security broker dealers.

[Table 2]

Columns 2-4 of Table 2 give the *CoVaR*s, and columns 5-8 the *t-statistic*. Consider column (2)/row (2) of Table 2. This gives the *CoVaR* of investment banks conditional on commercial bank distress. We run a 5% quantile regression of each investment bank on the value weighted commercial bank index and compute the conditional *VaR* of the investment banks conditional on commercial banks being at the worst 5%. We then compute the percent increase of this conditional *VaR* for each of the investment banks relative to the unconditional *VaR*, take the value weighted average across investment banks, and report it in the Table. The 45% *CoVaR*-increase of investment banks conditional on commercial banks means that the investment bank *CoVaR* is $(1+45\%)\cdot(-13.69\%) = -19.86\%$. In column (2)/row (3) we report the average percentage *CoVaR* increase of individual investment banks relative to the investment bank index (where the average is again value weighted). The percentage *CoVaR*-increase of 24% indicates that individual investment bank *VaR*s increase on average from -13.69% to $(1+24\%)\cdot(-13.69\%) = -16.99\%$.

We find that investment bank tail risk significantly increases conditional on distress of other investment banks, conditional on distress of commercial banks, and conditional on hedge fund distress. Commercial bank *VaR*s significantly increase after conditioning on investment bank distress, but not after conditioning on hedge fund distress. Distress of the hedge fund universe increases the tail risk of the individual hedge fund strategies, but investment and commercial bank distress does not lead to an increased hedge fund VaR.

In Panel B of Table 2 we report the *CoVaR* of commercial banks conditional on security broker dealer distress (column (3)/row (4)), and vice versa (column (2)/row (5)) for the longer time period 1926 – 2008. As in the shorter sample of Panel A, we find significant $CoVaR$ increases of similar orders of magnitude.

Note that the $CoVaR$ matrix unlike a correlation coefficient matrix is not symmetric. This makes sense that distress of one sector might cause distress in another sector but not vice versa.

2.5 Reasons for *CoVaR* Increase

The Value-at-Risk after conditioning on an adverse event for the index changes for at least three reasons. If the returns of a particular hedge fund strategy, investment/commercial bank is positively correlated with the index, the conditional mean return is naturally lower than the unconditional one. This leads to a higher $CoVaR$. Conditioning in general also lowers uncertainty since conditional variance is typically lower the variance of an unconditional return. This should lower the $CoVaR$. However, with heteroskedasticity, it can be the case that for low index returns, the return distribution of a particular hedge fund style or investment/commercial bank is more volatile. This leads to a higher $CoVaR$. Our quantile regression approach picks up the heteroskedasticity aspect (see Appendix), while a simple OLS approach under the homoskedasticity assumption does not. To see whether our $CoVaR$ results are purely driven by the mean-effect, we also calculate the $CoVaR$ that would arise if we assume that returns are normally distribution with homoskedasticity. More specifically we compute the OLS-$CoVaR$ using the sensitivity from an OLS regression, assume that shocks have a normal distribution, and condition on the fifth percentile of the right hand side portfolio. In Table 3, we report the percent increase of the $CoVaR$ estimated from the quantile regression (as in Table 2) minus the percentage $CoVaR$ increase estimated from an OLS regression.

[Table 3]

We can see from Table 3 that the quantile regression based estimates of the *CoVaR* are generally higher than the OLS-*CoVaR*, indicating that the quantile regression captures the increased heteroskedasticity of returns in the lefts tail. Column (2) indicates that the quantile *CoVaR* is significantly higher than the OLS-*CoVaR* for investment banks, conditional on any of the other institutions being in distress. For commercial banks and hedge funds, only distress within their own industry is associated with higher quantile *CoVaRs* relative to the OLS-*CoVaRs*. Our interpretation of these findings is that the *CoVaR* is a better method to estimate conditional tail risk, as it takes time variation of conditional heteroskedasticity into account. An alternative test for hetereoskedasticity that follows steps outlined in the appendix would lead to a similar conclusion.

2.6 Predictive *CoVaRs*

So far we focused on contemporaneous relationship between returns. Next, we incorporate quantile regressions into a Granger causality test to determine whether certain index returns predict distress in other financial intermediaries (in the sense of an increased Value-at-Risk), and vice versa. More specifically, we run two quantile regressions:

$$R_t^i = \alpha_q^{ij} + \gamma_q R_{t-1}^i + u_t^i \tag{4}$$

$$R_t^i = \alpha_q^{ij} + \beta_q^{ij} R_{t-1}^j + \gamma_q R_{t-1}^i + u_t^{ij} \tag{5}$$

We first compute the VaR^i from Equation (4) conditional on R_{t-1}^i being at the unconditional *VaR* of i. This is the *VaR* conditional on an institution/index having experienced a bad shock in the previous month. We then compute the "predictive 5%-*CoVaR*" as percent increase over the latter *VaR*, conditional on institution/index j having also experienced a tail event in the previous month. We report the results in Table 4.

[Table 4]

Our findings, presented in Table 4, show that hedge fund distress predicts a statistically significantly higher Value-at-Risk in the investment banking sector. The converse and a link to the commercial banking sector is not statistically significant, which is most likely due the fact that at the beginning of our data sample 1994, the interdependence between hedge funds and commercial banks was weaker than it is today. As commercial banks are entering more and more into the investment banking business (whose trading resembles to a large extent that of hedge funds), we would expect that the predictable risk spillovers from hedge funds to investment banks that we document might also show up for commercial banks.

By comparing column (1) of Tables 2 and 4 we can see that distress within institutional classes do predict higher tail risk within that class in the following month. For example, the predictive VaR for investment banks is -15.09% (Table 4, column 1, row 2), compared to an unconditional VaR of -13.69% (Table 4, column 1, row 2), representing an $15.09/13.60 - 1 = 11\%$ increase.

3 Tail Spillover Risk Factors

Having established that Value-at-Risk of institution i increases when the index return j is in distress, in this section we identify factors that explain this risk spillover effects. We argue that a factor structure explains this risk spillover, if the *CoVaR* after off-loading the risk associated with these factors roughly coincides with the unconditional off-loaded *VaR*. That is, if the risk spillover for residuals of the quantile regression is much lower compared to the dependence of the raw returns. We first introduce our six factors, before creating offloaded returns.

3.1 Description and Data

We select six factors that capture the increase in comovement across hedge fund styles' VaRs. All of them have solid theoretical foundations, capturing certain aspects of risks and hence, are not simply due to data mining. They are also liquid and easily tradable. We restrict ourselves to a small set of seven risk factors to avoid overfitting the data. All data are monthly from 04:1986 to 05:2008. Our factors are:

(i) CRSP *market return* in excess to the 3-month bill rate reflecting the equity market risk. The Center for Research in Security Prices (CRSP) market index is a broad benchmark reflecting the value weighted of all publicly traded securities;

(ii) *VIX* straddle excess return to capture the implied future volatility in the stock market. This implied volatility index is available on Chicago Board Options Exchange's website. To get a tradable excess return series we calculate the straddle return of a hypothetical at-the-money straddle position that is based on the VIX implied volatility and substract the 3-month bill rate.

(iii) the *variance swap return* to capture the associated risk premium for risky shifts in volatility. The variance swap contract pays off the difference between the realized variance over the coming months and its delivery price at the beginning of the month. Since the delivery price is not commonly observable over our whole sample period, we use – as is common practice – the VIX squared normalized to 21 trading days, i.e. $(\text{VIX}*21/360)^2$. The realization of the index variance is computed from daily S&P 500 index data for each month. Note also since the initial price of the swap contract is zero, returns are automatically excess returns.

(iv) a short term *"liquidity spread"*, defined as the difference between the 3-month repo rate and the 3-month bill rate measures the short-term counterparty liquidity risk. We use the 3-month general collateral repo rate that is available on Bloomberg, and obtain the 3-month Treasury rate from the Federal Reserve Bank of New York.

In addition we consider the following two fixed-income factors that are known to be indicators in forecasting the business cycle and also predict excess stock returns (Estrella and Hardouvelis (1991), Campbell (1987), and Fama and French (1989)).

(v) the return to the *slope of the yield curve*, measured by the yield-spread between the 10-year Treasury rate and the 3-months bill rate.

(vi) the return to the *credit spread* between BAA rated bonds and the Treasury rate (with same maturity of 10 years).

The last two factors are from the Federal Reserve Board's H.15 release. Table 5 gives the summary statistics for the risk factors.

[Table 5]

The literature has studied related factors. Boyson, Stahel, and Stulz (2006) use the S&P500, Russell 3000, change in VIX, FRB dollar index, Lehman US bond index and the 3-Month Bill return as factors, but – unlike our study – they do not find a link between these factors and contagion. Agarwal and Naik (2004) also focus on tail risk. In addition to out of the money put and call market factors they use the Russell 3000, MSCI excluding US (bonds), MSCI emerging markets, HML, SMB, MOM, Salomon Government and corporate bonds, Salomon world government bonds, Lehman high yield, Federal Reserve trade weighted dollar index, GS commodity index and change in default spread. Factors used in Fung and Hsieh (1997, 2001, 2002, 2003) differ depending on the hedge fund style they analyze. An innovative feature of their factor structure is to incorporate lookback options factors that are intended to capture momentum effects. We opted not to include this factor since restricted ourselves only to highly liquid factors. Fung, Hsieh, Naik, and Ramadorai (2008) try to understand performance of fund of fund managers. They employ the S&P 500 index as factor; a small minus big factor; the excess returns on portfolios of lookback straddle options on currencies, commodities and bonds; the yield spread – our factor (v) – and the credit spread – our factor (vi). Finally, Chan, Getmansky, Haas, and Lo (2006) use the S&P 500 total return, bank equity return index, the first difference in the 6-months LIBOR, the return on the U.S. Dollar spot rate, the return to a gold spot price index, the Dow Jones / Lehman Brothers bond index, Dow-Jones large cap - small cap index, Dow Jones value minus growth index, the KDP high yield minus U.S. 1-year Treasury yield, the 10-year Swap / 6-month Libor spread, and the change in CBOE's VIX implied volatility index. Bondarenko (2004) introduced the Variance swap contract as a new factor.

3.2 Off-loaded Returns

Having specified risk factors, we study how offloading tail risk explained by the six risk factors affects risk spillovers as measured by $CoVaR$s. We construct "5%-quantile offloaded returns" in the following way. We 5%-quantile-regress the excess return of each bank or hedge fund style on the risk factors, and call the constant plus the residual of that regression the offloaded return. This residual is a return as all of the factors are excess returns, i.e. zero investment portfolios, and the regression slopes can be interpreted as portfolio weights of a tail risk offloading strategy and VaR of the offloaded returns stays constant as one varies the factors.

Table 6 gives the summary statistics for the offloaded returns of different institutions and styles. Unfortunately, we cannot offload over the longer time period since 1926 as the volatility risk factors and the repo spread are not available for a longer history.

[Table 6]

The following differences between Tables 1 and 6 stand out: First, offloading the risk associated with our factors markedly reduces average returns and Sharpe ratios for commercial banks and hedge funds. The CAPM-α of hedge funds drops notably after offloading the risk associated with our factors. The average CAPM for hedge funds declines from a statistically significant .38% to $-.15\%$. The kernel densities of Figure 1 reveal that offloading reduces the fat left tail, but does not affect the right tail much. Figure 1 also shows that the average of the return distribution is shifted to the left, indicating that there is a tail risk-average return tradeoff: institutions can reduce tail risk, but have to give up average return.

[Figure 1]

3.3 *CoVaRs* of Off-loaded Returns

The percentage increase in *CoVaR* over the unconditional *VaR* for offloaded returns is given in Table 6. We can see that tail risk offloading eliminates the risk spillovers to investment banks (from both commercial banks and hedge funds) that is documented in Table 2. For total returns we find that the CoVaR increase of investment banks is 45% and 61% conditional on commercial bank and hedge fund distress, respectively. For offloaded returns, we do not find such a risk spillover to investment banks (Table 7). We also find that tail risk offloading with the systematic risk factors eliminates the risk spillover from investment banks to commercial banks.

[Table 7]

Among hedge fund styles, tail risk offloading also makes risk spillovers among hedge fund styles statistically insignificant. For excess returns, Table 2 shows an average CoVaR percent increase of 48% which is statistically significant with a *t-statistic* of 2.84. After tail risk offloading, the risk spillovers among styles decline to an insignificant 10%.

Tail risk offloading reduces the risk spillovers among commercial and investment banks, but does not eliminate them. In particular, by again comparing Tables 2 and 7s, we can see that risk spillovers are reduced from 43% to 30% for commercial banks and from 24% to 14% for investment banks. However, these spillovers are still statistically significant. We are thus missing a risk factor that allows the offloading of banking risk. We tried a number of commonly used additional risk factors (such as Fama-French, momentum, and reversal factors, other credit and liquidity spreads, foreign exchange returns, and additional option factors but have not been able to identify factors that can be useful in offloading the risk spillovers among banks).

We report the quantile *CoVaRs* relative to the OLS-*CoVaRs* in Table 8 and find that the quantile based measure of spillover risk is generally lower for the offloaded returns. This is the opposite of the result that we presented in Table 3. We find this result as offloading is asymmetric, and primarily reduces the left tail. The OLS based spillover measure overestimates the left tail, as it does not take into account that offloaded returns are more positively skewed.

[Table 8]

3.4 Incentives to Offload Tail Risk

Section 2 documents tail risk spillovers among financial institutions during times of distress. Section 3 identifies tradable factors that explain a large part of these risk spillovers. Do financial institutions have incentive to offload their tail risk, thus reducing the potential for spillover?

Hedge fund managers, investors, banks, or fund of fund managers can offload some of the tail risk with tradable risk factors without incurring large trading costs since our factors tradable and highly liquid. Furthermore, our offloading strategy is α-neutral. However, comparing Tables 1 and 6 shows that offloading markedly reduces the average monthly return for most institutions, particularly hedge funds. Stated differently, trading out of tail risk, and consequently out of spillover risk, is costly in terms of average returns. There appears to be a risk-return trade-off between returns and conditional Value-at-Risk.

4 Robustness

4.1 Alternative measures of risk spillovers

The comparison of q-sensitivities (quantile regression coefficients) across different quantiles q can be interpreted as a comparison of dependence across states of the world. In Figure 2, we plot the average sensitivities among hedge fund styles for all quantiles between 5% and 95% for total returns, OLS offloaded returns, and 5% offloaded returns. The OLS offloaded returns are constructed as the OLS alpha plus the residual relative to the six risk factors. The plot shows that the sensitivities across quantiles is relatively flat for the 5%-offloaded returns. In contrast, average sensitivities are sharply decreasing along the quantiles for the total returns, and are also decreasing for the OLS offloaded returns.

[Figure 2]

Instead of looking at sensitivities across states of the world, we can also investigate the evolution of dependence over time. To do so, we estimate a multivariate BEKK-ARCH(12) model, and extract the evolution of covariances across hedge fund strategies over time. We plot the average of the covariances across the ten strategies in Figure 3.

[Figure 3]

The covariances for the 5%-offloaded returns are clearly less volatile than for the total returns. In particular, estimated average covariances spiked during the LTCM crisis in the third quarter of 1998, and in January 2000. In contrast, the average covariances of 5%-offloaded returns increased much less during those volatile times.

4.2 Alternative risk measures

Our main results were derived for 5%-*VaRs* and 5%-*CoVaRs*. We chose the 5-th percentile for data reasons: for hedge funds, only data since 1994 is available. However, for commercial and investment banks, we can analyze spillover risk since 1926, so that we can estimate *VaR*s and *CoVaR*s for lower percentiles. In Table 9, we re-estimate Panel B of Table 2 for 1%-*VaRs* and 1%-*CoVaRs*. We find significant risk spillovers between commercial banks and security broker dealers for the first percentile. The *CoVaR* percent increase is smaller in magnitude for the first compared to the fifth percentile. However, it is highly significant for the spillover from commercial to investment banks, and significant at the 7% for the reverse (with a t-stat of 1.89).

[Table 9]

Value-at-Risk – our main measure of tail risk – is only one possible characterization of tail risk. Many alternative measures have been proposed. A particularly appealing measure of tail risk that has been proposed in the literature Artzner, Delbaen, Eber, and Heath (1999) is expected shortfall. It is defined as the average loss below the VaR. As robustness check, we calculate an expected shortfall spillover measure as the average *CoVaR* for 1%, 2%, 3%, 4%, and 5%. Panel B in Table 9 shows that we also find significant risk spillovers using the expected shortfall measure.

5 Risk Management and Regulatory Implications

5.1 Risk and Portfolio Management

CoVaR can be used to enhance portfolio management. For example, a fund of fund manager can estimate the extent to which individual hedge funds in a given portfolio are susceptible to risk spillovers. Instead of drawing an efficient frontier in average return – *VaR* space, the manager can choose portfolios in average return – *CoVaR* space. Such a procedure allocates additional risk to funds that are likely to be particularly distressed during times of heightened hedge fund volatility.

Our *CoVaR* risk measures is also useful for risk managers of trading floors who want to evaluate the interrelatedness of trading desks. When aggregating *VaR*s of individual trading desk, risk managers have to compute the diversification benefit. Computationally, aggregate *VaR*s are always smaller than simple sums of *VaR*s, once diversification benefits are taken into account. It should be noted that *CoVaR*s measure the potential for risk spillovers, not the diversification benefit. From a statistical point of view, *CoVaR*s can be either smaller or larger than *VaR*s. However, empirically, we have uncovered that *CoVaR*s tend to be larger than *VaR*s. So even if diversification leads to a reduction of aggregate *VaR*s relative to the sum of individual *VaR*s, *CoVaR*s can indicate that such diversification benefits might be offset by risk spillover effects.

5.2 Regulation and Systemic Risk

The credit and liquidity crunch of 2007/08 has underscored fundamental problems in the current regulatory set-up. When regulatory capital and margins are set relative to *VaR*s, forced unwinding of one institution tends to increase market volatility, thus making it more likely that other institutions are forced to unwind and delever as well. In equilibrium, such unwinding gives rise to a margin spiral / adverse feedback loops. An economic theory of such amplification mechanisms are provided by Brunnermeier and Pedersen (2007) and Adrian and Shin (2008). These "adverse feedback loops" were discussed by the Federal Open Market Committe in March 2008, and motivated Federal Reserve Chairman Ben Bernanke to call for regulatory reform.[7] Our *CoVaR* measure provides a potential remedy for the margin spiral, as the measure takes the volatility spillovers which give rise to adverse feedback loops explicitly into account. We propose to require institutions to hold capital not only against their *VaR*, but also against their *CoVaR*. "Crowded trades" such as the on-the-run/off-the-run trades that preceeded the LTCM crisis, or the short-financials/long-oil trade of the spring of 2008, would be penalized by capital requirements.

For risk monitoring purposes, *CoVaR* is a parsimonious measure for the potential of systemic financial risk. Institutions that monitor systemic risk—for example the

[7] See http://www.federalreserve.gov/monetarypolicy/fomcminutes20080318.htm. and http://www.federalreserve.gov/newsevents/speech/bernanke20080822a.htm.

Federal Reserve and other central banks around the world, the International Monetary Fund, and the Bank for International Settlement—have traditionally followed the evolution of *VaR*s of the financial sector. These institutions have also developed measures of system risk based on time varying second moments, estimates of exposures to different risk factors, and financial system tail risk measures. The advantage of using *CoVaR* is that it is tightly linked to *VaR*, the predominant risk measure.

6 Conclusion

During financial crisis or periods of financial intermediary distress, tail events tend to spill over across financial institutions. Such risk spillovers are important to understand for portfolio managers, risk managers, and supervisors of financial institutions. The ability to monitor and potentially hedge risk spillovers can help to optimize portfolio performance, to set risk limits and margins, and to adequately regulate institutions.

We find statistically and economically significant risk spillovers across institutions. We document that the spillover risk across institutions and across hedge fund styles can be hedged by offloading tail risk via tradable risk factors. However, the offloading comes at the cost of lower average returns for some financial institutions, particularly for hedge funds.

A Appendix

This appendix is a short introduction to quantile regressions in the context of a linear factor model. Suppose that excess returns R_t have the following (linear) factor structure:

$$R_t = \gamma_0 + X_t\gamma_1 + (\gamma_2 + X_t\gamma_3)\,\varepsilon_t \tag{6}$$

where X_t is a vector of risk factors. Factors are assumed to be excess returns. The error term ε_t is assumed to be i.i.d. with zero mean and unit variance and is independent of X_t so that $E[\varepsilon_t|X_t] = 0$. Our returns are generated by a process of the "location-scale" family, so that both the conditional expected return $E[R_t|X_t] = \gamma_0 + X_t\gamma_1$ and the conditional volatility $Vol_{t-1}[R_t|X_t] = (\gamma_2 + X_t\gamma_3)$ depend on a set of factors. The coefficients γ_0 and γ_1 can be estimated consistently via OLS:[8]

$$\hat{\gamma}_0 = \alpha_{OLS} \tag{7}$$

$$\hat{\gamma}_1 = \beta_{OLS} \tag{8}$$

We denote the cumulative distribution function (cdf) of ε by $F_\varepsilon(\varepsilon)$, and the inverse cdf by $F_\varepsilon^{-1}(q)$ for percentile q. It follows immediately that the inverse cdf of R_t is:

$$\begin{aligned} F_{R_t}^{-1}(q|X_t) &= \gamma_0 + X_t\gamma_1 + (\gamma_2 + X_t\gamma_3)\,F_\varepsilon^{-1}(q) \\ &= \alpha(q) + X_t\beta(q) \end{aligned} \tag{9}$$

[8] The volatility coeffients γ_2 and γ_3 can be estimated using a stochastic volatility or GARCH model if distributional assumptions about ε are made, or via GMM. Below, we will describe how to estimate γ_2 and γ_3 using quantile regessions, which do not rely on a specific distribution function of ε.

where

$$\alpha(q) = \gamma_0 + \gamma_2 F_{\varepsilon}^{-1}(q) \tag{10}$$

$$\beta(q) = \gamma_1 + \gamma_3 F_{\varepsilon}^{-1}(q) \tag{11}$$

with quantiles $q \in (0,1)$. We also call $F_{R_t}^{-1}(q|X_t)$ the conditional quantile function and denote it by $Q_{R_t}(q|X_t)$. From the definition of VaR:

$$VaR_q|X_t = \inf_{VaR_q} \{\Pr(R_t \leq VaR_q|X_t) \geq q\} \tag{12}$$

follows directly that

$$VaR_q|X_t = Q_{R_t}(q|X_t) \tag{13}$$

the q-VaR in returns conditional on X_t coincides with conditional quantile function $Q_{R_t}(q|X_t)$. Typically, we are interested in values of q close to 0, or particularly $q = 1\%$. Note that by multiplying the (absolute value of the) VaR in return space the by hedge fund capitalization gives the VaR in terms of dollars.

We can estimate the quantile function via quantile regressions:

$$\left[\alpha_q, \beta_q\right] = \underset{\alpha_q, \beta_q}{\arg\min} \sum_t \theta_q\left(R_t - \alpha_q - X_t \beta_q\right) \text{ with } \theta_q(u) = (q - I_{u \leq 0})\, u \tag{14}$$

See Koenker and Bassett (1978). Review Koenker and Bassett (1978) and Chernozhukov and Umantsev (2001).

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Figure 1: Kernel Densities of Total and 5%-Offloaded Returns

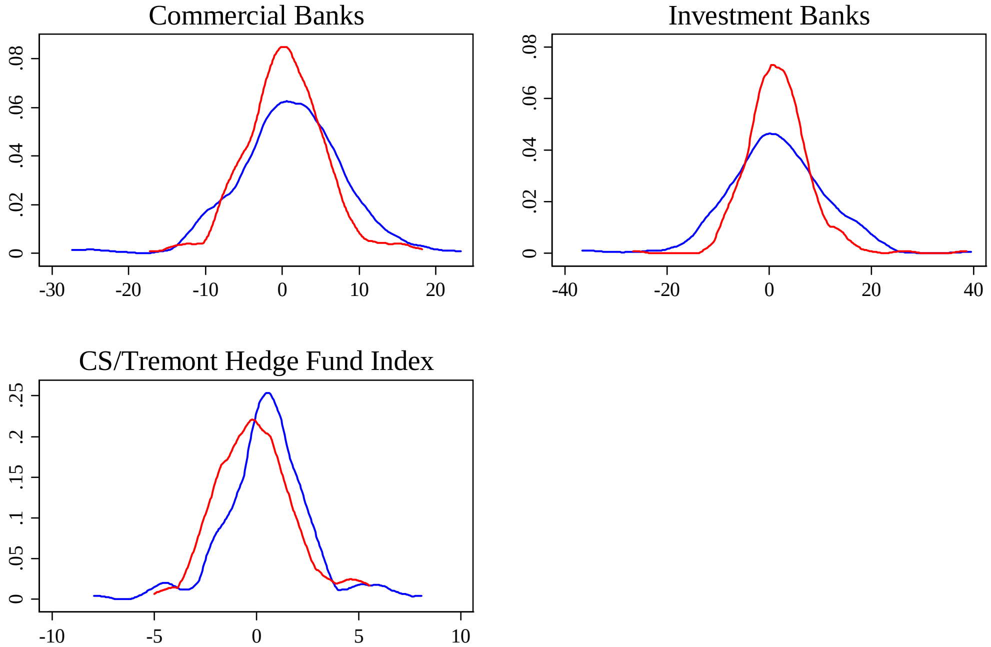

Figure 2: Average q-Sensitivities by Quantiles

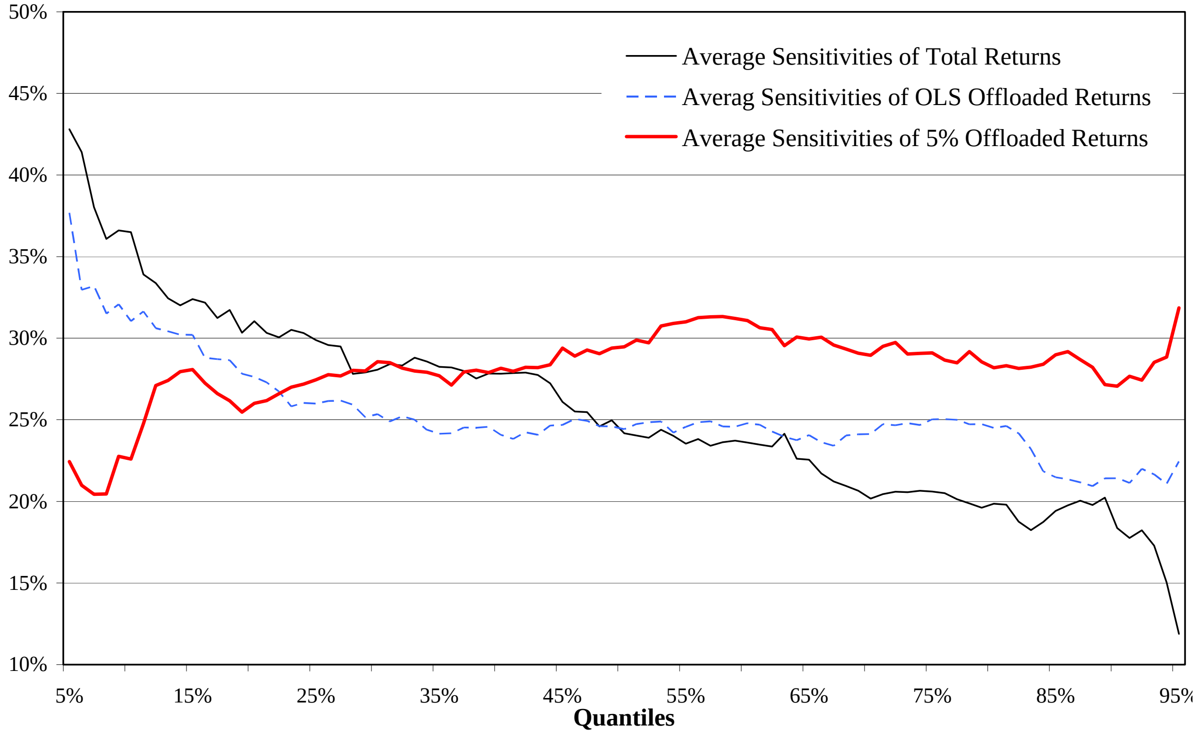

Figure 3: Average GARCH Covariances over Time

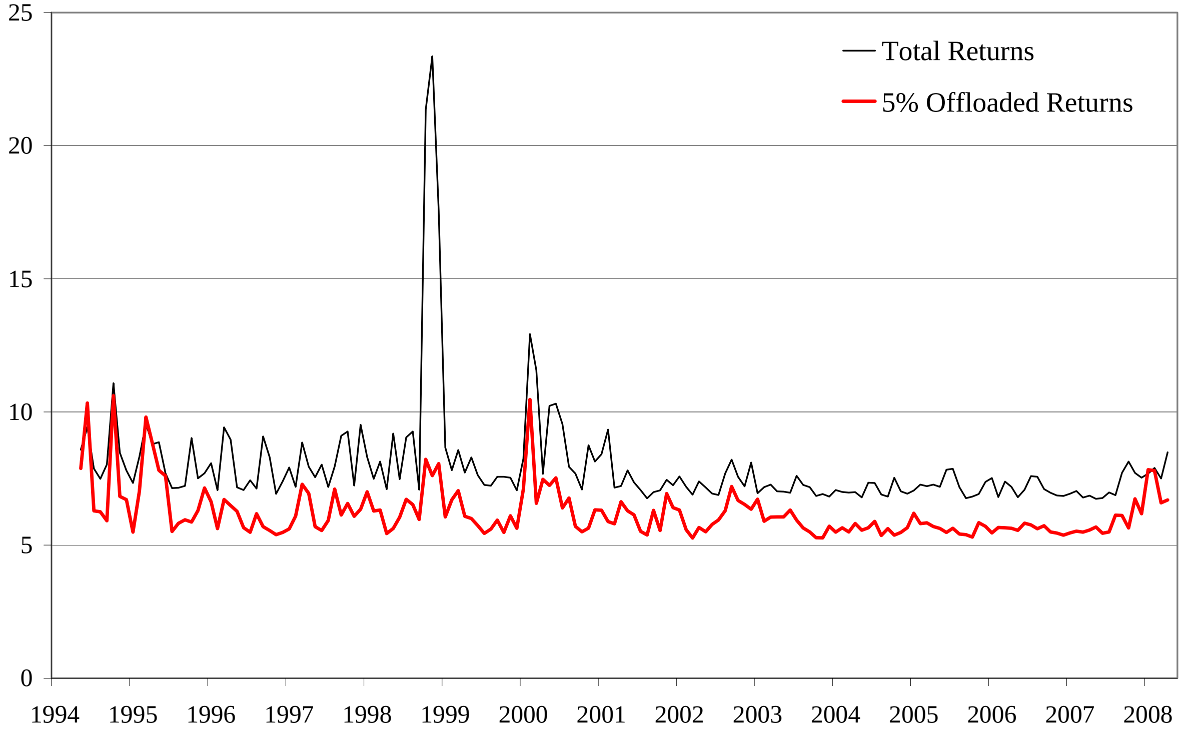

Table 1: Summary Statistics of Monthly Excess Returns

Panel A reports summary statistics for five commercial banks (Bank of America, Citibank, J. P. Morgan Chase, Wachovia, and Wells Fargo), five investment banks (Bear Stearns, Goldman Sachs, Lehman Brothers, Merrill Lynch, and Morgan Stanley), and the ten hedge fund style indices from Credit Suisse / Tremont. Panel B reports summary statistics for the commercial bank portfolio and the security broker dealer portfolio of Ken French's 49 industry portfolios. The return data for commercial and investment banks / security broker dealers are from CRSP. All returns are monthly, in excess of the three month Treasury bill rate. The Sharpe ratio is the ratio of mean excess returns to the standard deviation of excess returns. The skewness (skew), kurtosis (kurt), and first and fifth percentiles (1% and 5%).

Panel A: Institutions	Data range	Obs	Sharpe	Mean	Std Dev	CAPM α	Skew	Kurt	1%	5%
Five Large Commercial Banks	04/1986-03/2008	264	0.15	1.04	6.90	0.41	-0.36	4.80	-22.43	-9.87
Five Investment Banks	04/1986-03/2008	264	0.15	1.44	9.49	0.43	-0.14	4.80	-26.51	-12.33
Ten CSFB/Tremont Hedge Fund Styles	01/1994-05/2008	173	0.26	0.55	2.14	0.38 ***	-0.01	5.44	-5.12	-2.61

Panel B: Portfolios	Data range	Obs	Sharpe	Mean	Std Dev	CAPM α	Skew	Kurt	Min	5%
Commercial Bank Portfolio	07/1926-03/2008	981	0.13	0.93	7.10	0.28 **	0.24	8.20	-21.34	-9.74
Security Broker Dealer Portfolio	07/1926-03/2008	981	0.11	0.84	7.82	0.02	0.57	12.58	-21.67	-11.34

Table 2: 5%-CoVaRs

This table reports the percentage increase of the five percent Value-at-Risk for the returns of the left column conditional on the fifth percentile of the returns of the top row, relative to the unconditional 5% Value-at-Risk (reported in the first column). The t-stats test the null hyothesis that the percentage CoVaRs increase relative to the unconditional VaRs are zero. Standard errors are generated via bootsrap with 200 draws.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		5%-VaR	5%-CoVaR / 5%-VaR percent icrease				t-stats		
	Panel A: Institutions		CB	IB	HF		CB	IB	HF
(1)	Commercial Banks (CB)	**-12.23**	**43**	**29**	18	**-12.85**	**5.01**	**3.73**	0.94
(2)	Investment Banks (IB)	**-13.69**	**45**	**24**	**61**	**-7.86**	**5.03**	**3.14**	**4.13**
(3)	CSFB/Tremont Hedge Fund Styles (HF)	**-2.40**	27	23	**48**	**-9.24**	1.40	1.13	**2.84**
		5%-VaR	5%-CoVaR / 5%-VaR percent increase				t-stats		
	Panel B: Portfolios 1926-2008		CB	IB	HF		CB	IB	HF
(4)	Commercial Bank Portfolio (CB)	**-10.13**	.	**43**	.	**-17.84**	.	**6.15**	.
(5)	Security Broker Dealer Portfolio (IB)	**-11.83**	**37**	.	.	**-17.37**	**5.06**	.	.

Table 3: 5%-CoVaRs versus OLS-CoVaRs

This table reports the percentage increase of the 5%-quantile CoVaR relative to the 5%-OLS CoVaR. The t-statistic tests the null hyothesis that the percent increase of quantile CoVaRs relative OLS CoVaRs is zero. Standard errors are generated via bootsrap with 200 draws.

	5%-CoVaR / OLS-CoVaR percent increase			t-stats		
Panel A: Institutions	CB	IB	HF	CB	IB	HF
Commercial Banks (CB)	**18**	4	10	**2.64**	0.53	0.71
Investment Banks (IB)	**15**	**12**	**32**	**1.91**	**1.83**	**2.57**
CSFB/Tremont Hedge Fund Styles (HF)	21	17	**34**	1.22	0.99	**2.48**

	5%-CoVaR / OLS-CoVaR percent increase		t-stats	
Panel B: Portfolios 1926-2008	CB	IB	CB	IB
Commercial Bank Portfolio (CB)	.	**16**	.	2.29
Security Broker Dealer Portfolio (IB)	11	.	1.35	.

Table 4: Predictive 5%-CoVaRs

This table reports a predictive 5%-VaR and 5%-CoVaRs. To calculate the 5%-VaR, the returns of the institutions / hedge fund styles of the left column are quantile regressed on their lagged value. Then the predicted value is computed with the unconditional VaR as the value for the lagged variable. For the predictive CoVaR, the institutions / styles of the left column are regressed on their own lagged return, and the lagged return of the index of the top row. Then the predicted value is calculated by replacing both right hand side variables by their unconditional VaR. The percentage increase of the predictive CoVaR relative to the predictive VaR is reported in the Table. Standard errors are computed via bootstrap.

	5%-VaR	5%-CoVaR / 5%-VaR percent increase			t-stats			
Panel A: Institutions		CB	IB	HF		CB	IB	HF
Commercial Banks (CB)	**-13.90**	-3	-2	-16	**-8.58**	-0.61	-0.17	-1.02
Investment Banks (IB)	**-15.09**	4	5	**32**	**-4.27**	0.49	0.68	**2.83**
CSFB/Tremont Hedge Fund Styles (HF)	**-3.30**	-2	2	3	**-6.57**	-0.28	0.23	0.41

	5%-VaR	5%-CoVaR / 5%-VaR percent increase		t-stats		
Panel B: Portfolios 1926-2008		CB	IB		CB	IB
Commercial Bank Portfolio (CB)	**-11.49**	.	4	**-11.00**	.	0.72
Security Broker Dealer Portfolio (IB)	**-13.78**	-7	.	**-12.16**	-1.61	.

Table 5: Summary Statistics of Risk Factors

This table reports summary statistics for excess returns of six risk factors. The equity market return from the Center for Research in Security Prices (CRSP), in excess to the 3-month bill rate reflecting the equity market risk. The VIX straddle return is the return from buying at-the-money put and call options and is computed using the Black-Scholes (1973) formula with the CBOE's VIX implied volatility index, the 3-month Treasury rate, and the S&P500 index as inputs. The variance swap return is the difference between realized S&P500 variance from daily closing prices and the VIX implied variance. The repo Treasury spread is the difference between the three month general collateral Treasury repo rate (from Bloomberg) and the three month Treasury bill rate (from Federal Reserve Board's H.15 releases). The 10-year/3-month Treasury return is the return to the 10-year constant maturity Treasury bond (from H.15) in excess of the 3-month Treasury Bill. Moody's BAA - 10-year Treasury return is the return to Moody's BAA bond portfolio in excess of the return to the 10-year constant maturity Treasury return. All statistics are computed from April 1986 - May 2008.

	Mean	Std Dev	Skew	Kurt	1%	5%	Obs
CRSP Market Excess Return	0.54	4.34	-1.02	6.47	-10.76	-6.49	264
VIX Straddle Excess Return	-0.81	0.48	0.89	3.89	-1.65	-1.41	264
Variance Swap Return	-0.34	1.03	12.24	177.87	-0.85	-0.80	264
Treasury - Repo Rate	0.02	0.02	1.08	4.24	-0.01	0.00	264
10 Year - 3 Month Treasury Return	0.29	2.38	-0.33	3.10	-6.25	-3.67	264
Moody's BAA - 10 Year Treasury Return	0.14	1.31	-0.45	3.81	-3.48	-2.28	264

Table 6: Summary Statistics for Monthly 5%-Offloaded Returns

The table reports summary statistics for the tail risk offloaded returns of banking institutions and hedge fund styles. Offloaded returns are computed as the sum of the regression residual and the intercept from a 5%-quantile regression on the six risk factors from Table 4.

	Data range	Obs	Sharpe	Mean	Std Dev	CAPM α	Skew	Kurt	1%	5%
Five Large Commercial Banks	04/1986-03/2008	264	0.08	0.40	5.20	0.38	0.17	4.06	-12.73	-7.32
Five Investment Banks	04/1986-03/2008	264	0.29	1.80	6.24	1.70 ***	0.78	8.78	-10.41	-7.45
Ten CSFB/Tremont Hedge Fund Styles	01/1994-05/2008	172	-0.03	-0.05	1.90	-0.07	0.52	3.63	-4.24	-2.63

Table 7: Offloaded 5%-CoVaRs

This table reports the percentage increase of the five percent Value-at-Risk for the offloaded returns of the left column conditional on the fifth percentile of the returns of the top row relative to the unconditional 5% Value-at-Risk (reported in the first column). The Value-at-Risk is computed from the five percent pair wise quantile regressions (the slopes of these regressions are reported in Table 3). The p-values test the null hyothesis that average CoVaRs equal average VaRs and are generated via bootsrap with 200 draws.

	5%-VaR	5%-CoVaR / 5%-VaR percent increase			t-stats			
		CB	IB	HF		CB	IB	HF
Commercial Banks (CB)	**-7.86**	**30**	3	-8	-33.45	3.54	0.31	-0.93
Investment Banks (IB)	**-10.28**	3	**14**	0	-60.95	0.39	1.76	-0.03
CSFB/Tremont Hedge Fund Styles (HF)	**-2.36**	1	1	10	-35.25	0.14	0.08	1.61

Table 8: Offloaded 5%-CoVaRs versus OLS-CoVaRs

This table reports the percentage increase of the five percent Value-at-Risk for the offloaded returns of the left column conditional on the fifth percentile of the returns of the top row relative to conditional VaR computed from an OLS regression. The t-stats test the null hyothesis that average quantile CoVaRs equal average OLS CoVaRs and are generated via bootsrap with 200 draws.

	5%-CoVaR / OLS-CoVaR percent increase			t-stats		
	CB	IB	HF	CB	IB	HF
Commercial Banks (CB)	-7	**-20**	-2	-0.92	**-2.80**	-0.11
Investment Banks (IB)	-14	1	-1	-1.14	0.10	-0.07
CSFB/Tremont Hedge Fund Styles (HF)	3	2	-2	0.33	0.20	-0.20

Table 9: 1%-CoVaRs and Expected Shortfall 1926-2008

Panel A of this table reports the percentage increase of the one percent Value-at-Risk for the returns of the left column conditional on the fifth percentile of the returns of the top row relative to the unconditional 5% Value-at-Risk (reported in the first column).
Panel B reports the unconditional 5% expected shortfall (ES) in the first column, and the percent increase of the expected shortfall conditional on the portfolio of the top row being in the worst five percent of the return distribution as percent increase relative to the unconditional expected shortfall.

Panel A: 1%-CoVaR	1%-VaR	1%-CoVaR / 1%-VaR percent icrease		t-stats		
		CB	IB		CB	IB
Commercial Bank Portfolio (CB)	**-21.46**	.	**23**	**-9.06**	.	**1.89**
Security Broker Dealer Portfolio (IB)	**-22.46**	**38**	.	**-9.30**	**3.44**	.

Panel B: 5%-Expected Shortfall	5%-ES	5%-CoES / 5%-ES percent icrease		t-stats		
		CB	IB		CB	IB
Commercial Bank Portfolio (CB)	**-13.67**	.	**40**	**-13.98**	.	**6.74**
Security Broker Dealer Portfolio (IB)	**-16.01**	**37**	.	**-14.63**	**5.95**	.