Tail Risk at Banks

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Preliminary Version

Abstract

The recent financial crisis has shown anew that systemic bank crisis can have large spillovers to the real economy. For regulators, having an estimate of how much an individual bank is exposed to a market crash (tail risk) is important as it can help to identify potentially weak banks and it may help to understand what the determinants of tail risk are. The existing methodologies utilizing market data are all backward looking, which has the disadvantage that major changes either in the banking activity or the economic environment may not be captured promptly. In this paper we propose a forward looking way to measure banks' tail risk exposure using market data only. We estimate the exposures at the bank level and show that our estimate contains different information than for example the CAPM beta or a Quantile-beta. Moreover, we investigate the determinants of tail risk and find that especially non-traditional asset activities contribute to a bank's tail risk exposure. On the liabilites side we find that wholesale-like funding contributes to tail risk, too.

JEL classification:???

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1 Introduction

The recent financial crisis has shown anew that a systemic banking crisis, a situation in which many banks are in distress at the same time, can have large spillovers to the real economy. This is because in times of trouble the smooth functioning of the banking system is severely disturbed, which can lead to, for example, a credit crunch and later on a contraction of output in the economy. Therefore, knowledge about a bank's exposure to a market crash, i.e. tail risk, is important especially for financial supervisors for at least two reasons. First, it is important as a measure itself to identify potentially weak banks and put them under increased scrutiny, helping to prevent a crisis in the first place. Second, it enables the supervisor to better understand which activities particularly contribute to tail risk exposure. This knowledge may help to fine-tune supervision and regulation in order to prevent future crisis from happening.

Currently, supervisors and regulators obtain their information about the riskiness of a bank from, broadly speaking, two sources. They obtain a large body of information from the respective bank itself but they also rely on information from outside sources like, for example, the financial markets. While the information from banks form a crucial part of the evaluation process they are not free of any drawbacks. It has been shown that several informational items are under the discretion of banks and are used strategically by banks[1]. Moreover, most of this data is backward looking and available at a low frequency while ideally one would like to have forward looking estimates of risk at a higher frequency so that new information is readily incorporated. Lastly, the banks' information represents the banks' view and, by definition, may therefore not capture all the information that is out there. It may miss some important information such as informal information in the markets but also analyst reports, for example.

For these reasons, it may be very beneficial to consider market-based information in the supervisory and regulatory process, too. The recent literature provides evidence that market signals do indeed contain valuable information about banks' risks (for a brief overview see, for example, Birchler and Facchinetti (2007) and Knaup and Wagner (2009); for surveys, see Flannery (1998) and Flannery (2001)). In addition, Birchler and Facchinetti (2007) conclude that "supervisory information and market information are complementary sources of bank supervisory intelligence" as market signals contain "information which is not yet part of confidential supervisors' information. At the same time, market data do

[1]For the reporting of loan losses see, for example, Wall and Koch (2000) and Hasan and Wall (2004). On the actual provisioning for loan losses, see, for example, Laeven and Majnoni (2003). Huizinga and Laeven (2009) find evidence that banks use accounting discretion to overstate the value of their distressed assets.

not reflect all information available to supervisors."

The methods that use (or can be used with) market data to estimate banks' tail risk exposures can be classified as measuring either individual tail risk or systemic tail risk. While each measure has its specific advantages and drawbacks (see Section 2 for a more detailed discussion of selected measures) they all have one major drawback in common, namely that they are all backward looking. This means that each measure has to rely on the historical distribution of the relevant market data to either directly identify a tail event or obtain an estimate for a distributional assumption. This reliance can proof particularly troublesome after long periods of ease in which no tail event took place or when a bank makes structural changes to its business model so that the past behavior of, for example, the share price is no longer indicative of its future behavior.

This paper contributes to the literature by presenting a proposal for a forward looking way to measure tail risk exposure at banks. Tail risk exposure is defined as a bank's exposure to a general market crash (a severe downturn in the economy). By focusing on the exposure to a market crash, our proposal incorporates exposure to systemic risk since a market crash is likely to have systemically relevant consequences as many banks may get into distress at the same time when the economy contracts severely. A bank's exposure is estimated through a bank's share price sensitivity towards changes in the prices of a (relatively far) out of the money put option on the market (proxied by the S&P 500). This put only has a positive payoff when the market crashes so that news about tail (market crash) risk should be reflected in changes in the prices of this put option. The estimated sensitivity can be seen as the market's perception of a bank's tail risk exposure, which may be useful information for a regulator. It may give new insights of who is particularly exposed to a market crash well before the crash actually materializes and it may also help to understand which balance sheet activities contribute to tail risk exposure. Knowledge about both items may be used by a regulator to fine-tune regulation in order to decrease the likelihood and/or severity of a systemic crisis.

We estimate tail risk exposure for 209 of the largest commercial bank holding companies in the U.S. and find that there is considerable cross-sectional variation in perceived exposures to tail (market crash) risk. Moreover, we show that the information in our tail risk measure is not contained in normal times risk measures, which adds insights for the regulator about the different risk exposures of banks.

We also add to the literature of drivers of tail risk exposure by investigating the question of which banking activities are related to a bank's tail risk exposure. The existing literature is limited so far and mostly focuses on outright bank failures with only a few notable exceptions like, for example, DeJonghe (2008). In line with recent evidence, we find that variables proxying for traditional banking activities like, for example, the loan to asset ratio or loan quality proxies, are perceived to be less risky. Several non-traditional activities, on the other hand, are perceived to contribute to tail risk. In particular, we find that the return of assets, corrected for loan income, is related with a higher tail risk exposure as well as securities held for-sale, trading assets and derivatives used for trading purposes. Securitization and asset sale activities are in general not associated with an increase in tail risk exposure with the exception of the external credit exposure (for example credit enhancements to securitization products of other banks). Moreover, we find that size is negatively related to tail risk, which could reflect perceptions of Too Big To Fail. On the liabilities' side leverage turns out to be insignificant but controlling for leverage and the deposit to liabilities ratio, the ratio of time deposits above \$100.000 to total deposits is related with a higher tail risk exposure. Since these deposits are typically not insured, they can be seen as being similar to wholesale funding so that non-traditional activities on the liabilities' side seem to be related with tail risk exposure, too.

The paper is structured as follows. Section 2 briefly reviews the literature on (tail) risk measures and section 3 develops the methodology for measuring tail risk exposure in a forward looking manner. The theoretical properties of our measure are discussed in section 4, while section 5 presents the empirical analysis before section 6 concludes.

2 Literature on (Tail) Risk Measures

2.1 Idiosyncratic Measures

Value-at-Risk (VaR) is seen by many as the standard risk measure for financial risk management thanks to its conceptual and computational simplicity (Yamai and Yoshiba (2005)). VaR is defined as the worst loss over a given holding period within a fixed confidence level[2]. Despite its wide acceptance, the VaR concept has several shortcomings. Artzner et al. (1997, 1999), for example, note that VaR disregards any loss beyond the VaR level (it does not look into the tail) and thus does not capture tail risk. Moreover, but not central to our analysis, it is not a coherent risk measure since it does not take into account risk reduction through portfolio diversification.

To remedy these two problems, Artzner et al. (1997, 1999) propose the expected shortfall (ES) as an alternative risk measure that takes into account the extreme losses beyond VaR. The expected shortfall is defined as the expected loss conditional on the losses being beyond the VaR level[3]. Although the ES remedies the shortcomings of the

[2] See Standard & Poors (2005) for a brief overview and Jorion (2006) for a more detailed approach.

[3] Tasche (2002) notes that "Independently, ES was introduced in Rockafellar and Uryasev (2001) under

VaR, both concepts still can be seen as backward-looking in the sense that both need to rely on either historical or simulated data or input estimates.

Another frequently used market-based risk measure is Moody's KMV. Essentially, Moody's KMV is a distance to default measure that is turned into an expected default probability with the help of a large historical dataset on defaults. The distance to default is measured as the number of standard deviations by which the expected asset value exceeds the default point. A firm's one year expected default probability is then calculated as the fraction of those firms in previous years, which had the same distance to default and actually defaulted within one year (see Bohn and Crosbie (2003) for a detailed description). By its very nature, the KMV measure is not a tail risk measure itself but, according to Bohn and Crosbie (2003), it can be used for market crash simulations. A firm's exposure to a market crash is captured through the CAPM beta, which is used to simulate the decline in the asset value and thus the change in the distance to default.

Subordinated debt spreads are an alternative measure of a bank's default risk. The use of subordinated debt spreads as a disciplining device has been put forward in various proposals[4]. However, similarly to the KMV concept, subordinated debt spreads are not a direct tail risk measure. Contrary to the KMV methodology however, it is not possible to simulate market crashes, which make bond spreads even less suitable for tail risk analyses. In addition, according to Birchler and Facchinetti (2007), there exist some debt specific drawbacks like, for example, significant sytematic components and liquidity issues.

2.2 Systemic Measures

The literature on systemic risk measures is still relatively young and limited. One strand focuses on the exposure to systemic risk like, for example, the concept of tail-betas (see Hartmann et al. (2006).and Straetmans et al. (2008)). This concept uses extreme value theory to derive the probability that an individual bank's value declines dramatically in the presence of an extreme negative systematic shock. Potential drawbacks of this method are the need for large number of observations (at least 6 years of daily data) to get accurate estimates (DeJonghe (2008)) and its backward looking nature (a crisis needs to be identified ex post to calculate the co-crash probability).

Adrian and Brunnermeier's (2009) CoVaR concept goes one step further and estimates the contribution of each institution to the overall system risk. A bank's CoVaR is defined as the VaR of the whole financial sector conditional on the bank being at its own VaR level,

the notion Conditional value-at-risk (CVaR)". It is sometimes also known as "mean excess loss", "beyond VaR", or "tail VaR" (Yamai and Yoshiba (2005)).

[4] See Birchler and Facchinetti (2007) for a more detailed discussion.

that is, being in distress. The banks's marginal contribution to the overall systemic risk is then measured as the difference between the bank's CoVaR and the unconditional financial system VaR. This difference, ΔCoVaR, is usually positive since the financial system VaR is typically higher given that an institution is already in distress. Since CoVaR is based on the VaR methodology it also inherited the associated drawbacks, namely its backward looking nature and the fact that it does not look into the (left) tail of the distribution

3 Measuring Tail-Risk Using Put-Options Sensitivities

3.1 The Basic Idea

In this section we present the idea of a forward-looking way to measure tail risk using market data only. However, before we turn to the derivation we first need to define what we have in mind when we talk about tail risk. In this paper we define a bank's tail risk exposure to be the bank's exposure to a general market crash (a severe downturn in the economy). If the market crashes banks may suffer large, simultaneous losses on a number of loans and other asset items which may push them close to or into bankruptcy. However, the extent to which a bank suffers losses depends on its past actions, which determined its exposure to the market. To see this, consider two hypothetical banks.

Bank A invests mostly in traditional banking assets like, for example, loans to businesses and households. Moreover, it invests in assets that are mainly exposed to normal times risk, like, for example junior tranches of securitization products. These products lose in value already in normal times as soon as the first losses on the underlyings materialize. In addition to these assets, bank A insures itself against default by buying protection on its major assets whose default would push bank A into bankruptcy. Therefore, bank A's equity value moves relatively proportional to the market value in normal times but behaves less than proportional in market crash times, as its major assets are hedged.

Bank B, on the other hand, follows a different business strategy. It does have traditional assets like, for example, loans, but in addition, it also invests in assets that have a small and steady payoff in normal times but catastrophic losses when the market crashes. Examples would be selling protection in the credit default swap (CDS) market or buying a super senior tranche, which loses in value only when all other tranches already incurred a total loss. Bank B's equity value behaves similar to bank A's in normal times but it falls even more than proportionally in market crash times as it incurs extra losses in this scenario.

The development of the equity values is summarized in Figure 1. In normal times (market values above $\overline{x}$), the banks' equity values behave proportional to the market while in crash times (market values below $\overline{x}$) Bank A's (B's) equity should react less (more) than proportional to the market decline[5].Taken together, we can formulate the main idea underlying our analysis. If banks have a different exposure to tail (market crash) risk, their share price reaction to news about tail risk should be different. Before we test this hypothesis in section **??** and evaluate its informational content, let us express the main idea in a more formal manner.

- Insert FIGURE 1 about here -

3.2 The Derivation

The market is given by a representative firm with debt d and next period asset value x , which is distributed on $[0, \infty)$ with the density $\phi(x)$. We denote the asset value of the representative firm net of debt with $\widetilde{x} := x - d$. Similarly, bank i's asset value is denoted with y and its debt level with d_y. Bank i's equity value, which is equal to the asset value net of debt, is thus $\widetilde{y} := y - d_y$.

We define tail risk exposure as the exposure to a market crash, which means that tail-risk of banks kicks-in below market realizations of $\overline{x}$ (the crash threshold). Moreover, we hypothesize that above the crash threshold $\overline{x}$ bank values are identically distributed (in proportional terms) to the market while below $\overline{x}$ bank values are potentially more sensitive. In words, in normal times the market has values above $\overline{x}$ and the relationship between a bank's share price return and the market return can be captured by the well-known CAPM beta. The market crashes when it falls below $\overline{x}$ and in this scenario the relationship between a bank's share price return and the market return may not be captured adequately by the CAPM beta alone but an extra effect (the exposure to tail risk) may make the stock return more sensitive.

In particular, we assume that for $\widetilde{x} \geqslant \overline{x}$ a bank's equity value is equal to

$$\widetilde{y}(\widetilde{x}) = \eta \widetilde{x}^{\beta}, \tag{1}$$

while for $\widetilde{x} < \overline{x}$ it is equal to

$$\widetilde{y}(\widetilde{x}) = \eta \frac{\widetilde{x}^{\beta}}{(\frac{\overline{x} - \widetilde{x}}{\overline{x}} + 1)^{\gamma}}, \tag{2}$$

[5] From the discussion above, one can see that we pay particular interest to the equity reaction in crash times. Note, that the equity values might also react differently in normal times. Although the reaction in normal times is not our primary focus, we still control for this possibility in our analysis below.

where η accounts for size differences, β is the market beta of a bank and γ is the tail-risk exposure of a bank which comes on top of the normal times beta of a bank. For $\gamma > 0$ a bank has more tail-risk exposure than the market so that in crash scenarios ($\widetilde{x} < \overline{x}$) its equity value declines more than proportionally to the market. The opposite is true for $\gamma < 0$ while for $\gamma = 0$ we are back to the pure CAPM beta.

Identification of the tail risk news will happen through variations in the prices of a put option on the market. A put option on the market, which is far out of the money, represents market crash risk as it has a positive payoff only when the market crashes. News about tail (market crash) risk should hence be reflected in the price of such a put option. To be more precise, consider a put-option on the market with a strike price of exactly $\overline{x}$. This put will have a pay-off $p = 0$ in normal times ($\widetilde{x} \geqslant \overline{x}$) but a positive pay-off $p = \overline{x} - \widetilde{x}$ in the crash scenario ($\widetilde{x} < \overline{x}$). Using the pay-off properties of this put option we can combine equations (1) and (2) into one expression for a bank's equity value for any given realization of $\widetilde{x}$:

$$\widetilde{y}(\widetilde{x}) = \eta \frac{\widetilde{x}^{\beta}}{(\frac{p}{\overline{x}} + 1)^{\gamma}}. \tag{3}$$

Totally differentiating with respect to $\widetilde{x}$ and p and dividing by $\widetilde{y}$ yields

$$\frac{d\widetilde{y}(\widetilde{x})}{\widetilde{y}} = \beta \frac{d\widetilde{x}}{\widetilde{x}} - \gamma \frac{dp}{p + \overline{x}}. \tag{4}$$

Taking expectations, and assuming independence between expected changes in a variable and its level (that is, changes in $\widetilde{x}$ are not correlated with the level of $\widetilde{x}$, as would be the case under a random walk) we get approximately

$$\frac{dE[\widetilde{y}(\widetilde{x})]}{E[\widetilde{y}]} \approx \beta \frac{E[d\widetilde{x}]}{E[\widetilde{x}]} - \gamma \frac{E[dp]}{E[p] + \overline{x}}$$

Note, that under fairly priced debt we have that $E[\widetilde{x}]$ is the value of the market, $E[\widetilde{y}(\widetilde{x})]$ the value of a bank's equity and $E[p]$ the value of the market put option. Hence, denoting values with upper cases we can run the following regression:

$$\frac{dY}{Y} = \alpha + \beta \frac{dX}{X} - \gamma \frac{dP}{P + \overline{x}} + \varepsilon. \tag{5}$$

If share prices of banks with different market exposure react differently to news about tail (market crash) risk, this should be reflected in the gamma, which represent a bank's tail risk exposure over and above the S&P500 exposure.

3.3 Put Options on the S&P 500

In this subsection, the put option and the choice of its strike price will be discussed more in detail. As mentioned before, a put option on the S&P 500, which is far out of the money, represents tail (market crash) risk. Therefore, news about tail risk should influence the price of such a put option. This is true even if the market moves only within normal times risk, because even a small decline in the market (ceteris paribus) implies that the market moves closer to the crash area so that the probability of a crash (although still small) increases and the price of the put option increases, too. Similarly, even a small increase in the market reduces the probability of a crash and thus the price of the put option (ceteris paribus).

The S&P 500 was chosen as an underlying for the put options for several reasons. First, it is a very large and broad index and thus a good approximation of the market so that it has been established as the most often used proxy for the market. Second, the put options on this index are also actively traded and very liquid, which may not be the case for narrower indices. Third, due to its large size, it can be seen as an exogenous variable in the sense that a single bank is unlikely to have an influence on the S&P 500 in a constant, that is, daily basis.

The choice of the strike price is another issue that needs to be addressed. We could simply take one fixed strike price that is far enough out of the money throughout the whole sample period. This, however, introduces the problem that our measured intensity of tail risk changes when the level of the S&P500 changes. One solution to this problem would be a fixed percentage like, for example, 20% below the S&P500 level. This is not a viable solution yet, as one also needs to take into account that the price of an option changes with changes in the volatility of the underlying. Hence, the percentage would need to float with the volatility of the market. However, at this point it is not clear in what way the exact modeling choice may influence or even bias the results of the analysis. For this reason, we chose another route.

We set an artificial put price of 0.5, which is relatively out of the money[6] and thus representing tail risk. At day one we take the weighted average of the two closest put prices above and below 0.5 to replicate a price of 0.5. This enables us to calculate the implied strike. Next, given the weight, we calculate the put price (the weighted average) for day two and calculate the change of the price, dP, from day one to day two. After that, we calculate the weight at day two anew to obtain again a price of 0.5 and repeat the whole procedure to obtain the change in the weighted put price, dP, from day two to day three. This procedure is repeated for each day until the end of the sample period. It yields all the elements needed to calculate our proxy for tail risk news in equation (5), which we

[6]The implied strike is on average around 33% lower than the level of the S&P 500. In the rather tranquil times of 2006, the average implied strike was still around 28% below the S&P 500 while in the more turbulent times after June 2007 it was on average around 38% below the S&P 500.

call the percentage return of the adjusted put. The term adjusted is used since we need to correct for the level of the strike price, which may change over time due to changes in the weights and due to changes in the two underlying put options. As these two types of changes can occur each day, it is necessary to perform this simple calculation for each day in the sample period.

4 Discussion of the Theoretical Properties

The proposed methodology of estimating banks' tail (market crash) risk exposure with the help of put options on the market has, in theory, several attractive features. First, the proposed method is forward looking in the sense that it represents market expectations, which are reflected in option and share prices. Therefore, the assumption of backward looking methods, namely that the past performance of a bank stock is representative for its future behavior, is no longer crucial. This assumption was of particular concern for a period of crisis after a longer period of calm and for changes in the business model of a bank. In addition, the method does not require many years of past data to calculate tail risk estimates as do other methods like, for example, the extreme value theory based tail betas.

Second, this method should enable a regulator to identify exposed banks without even observing the actual event of a crisis. Already small changes in the put option prices in normal times may be enough to estimate the share price sensitivities and cross-sectionally identify the most exposed banks. This is in contrast to virtually all other measures considered above, as they either have to observe the event of a crisis directly or take a second best approximation like, for example, the largest share price decline in normal times in order to determine the tail risk exposure.

A third attractive feature is the computational simplicity and the reliance on market data only. This implies that the tail risk measure is available on a daily basis and that it represents the market's perception of risk at a bank. It thus offers a different point of view for the regulator compared to the view of the banks. This may be beneficial to the supervisor as the market's perception may be complementary in nature compared to the supervisor's information from banks (Birchler and Facchinetti (2007)).

Potential drawbacks, on the other hand, include inaccurate pricing issues and very specialized banks whose tail risk may not stem from market exposures. Inaccurate pricing due to, for example, bubbles or illiquidity in the share or option prices may affect the precision of the estimates. While the absolute level of the coefficients is likely to be affected, it is a priori not clear that the cross-sectional ranking is automatically affected. As long as a bubble in the stock markets affects all share prices in a similar manner, this may not be the case. It will become a concern however, once the precision of the estimates depends on certain bank characteristics, which may affect the cross-sectional comparison.

A second potential concern is the fact that banks may be exposed to tail risk of some other kind than market crashes. A bank may have a very low exposure to the general market but a high exposure to a very specialized market or investment product. In this analysis the bank would seem relatively less risky but in fact, it is not. While this concern arises by the very nature of the method design, it may in practice be less of a problem as a regulator may be informed about the degree of specialization and only a few banks might be that specialized. One potential solution to this issue would be to use a more specialized asset as the underlying for the put options, under the condition that the put options are still reasonably liquid. Note however, that this would move the whole focus of our analysis away from tail risk stemming from market crashes towards tail risk of some other kind.

The assumption that share prices are informative about banks' inherent risks is another point of consideration. The recent literature (see Birchler and Facchinetti (2007) and the references therein) provides ample evidence that market data can indeed be informative about bank risk. Note that we do not need to assume that equity markets are fully efficient and that prices reflect all available information (similar to the Moody's KMV method, see Bohn and Crosbie (2003)) but rather that it is difficult to consistently beat the market. Nevertheless, it is obvious that the precision of the signals increase with more market efficiency.

Although we already touched upon the differences of our method compared to the other (tail) risk measures, let us briefly summarize them. Our proposed gamma directly measures exposure to tail risk unlike distance to default, Moody's KMV, bond spreads and VaR. Moreover, it is forward looking contrary to the expected shortfall, CoVaR and tail betas, which all have to rely on the historical distribution to identify tail events. Another feature of our measure is that it does not reflect pure idiosyncratic risk at a bank, as the put option is on the market, which is proxied by the S&P500. In that sense it measures the sensitivity of a bank's share price to a general (severe) downturn in the market, making it a systemic risk measure. Since our gamma is focusing more on exposure rather than contribution to systemic risk, it is closer related to the tail beta concept, which measures the exposure to a market crash through the probability that a bank is in distress given that the market is in distress. One crucial difference to the tail betas is that our method is inherently forward looking. Compared to the CoVaR methodology, one has to note that CoVaR focuses on contributions to systemic risk while our gamma focuses more on the exposure to systemic risk. This implies that potential externalities among institutions are not considered here so that bank interlinkages cannot be measured.

One way to get closer to the interlinkages would be to use a banking index à la BKX as an underlying for the put options. This would narrow the tail risk exposure down to the banking sector but may reveal interlinkages better. One practical problem with this approach is that you need to utilize very liquid option data, otherwise your estimates may be unreliable. However, preliminary tests with BKX put options have shown that these option prices are far less liquid than S&P500 options. Due to these illiquidity concerns we decided to not further explore this avenue.

5 Empirical Analysis

5.1 Data

We collect daily data on banks' share prices and the S&P 500 for the period October 4^{th} 2005 until September 26^{th} 2008 via Datastream. The respective put option data on the S&P 500 (more details will follow below) for the same period is purchased from www.ivolatility.com. In addition, various balance sheet data are collected from the FR Y-9C Consolidated Financial Statements for Bank Holding Companies (BHCs). We focus on U.S. BHCs which are classified as commercial banks and for which data is fully available (the reason why we focus on the BHC instead of the commercial bank itself is that typically it is the BHC that is listed on the stock exchange). Excluded are those banks whose share price change is zero in more than 10% of the cases in order to prevent that liquidity issues affect the accuracy of the results. Moreover, foreign banks (even when listed in the U.S.) and pure investment banks are excluded, too. The final sample contains 209 Bank Holding Companies.

For the S&P 500 put options we obtain daily data on all out-of-the-money puts. However, a first inspection revealed that the 100er strikes (i.e. 500, 600, 700 etc.) are far more liquid than put options with other strike prices like, for example, 495. Therefore, we only use puts with 100er strikes to rule out liquidity concerns. The daily change in the put option and its implicit strike price are then calculated according to the procedure laid out above in section 3.3. To ensure that the remaining time to maturity has the lowest possible impact on the daily changes of the put, we create an "on-the-run" series. For example, for the last week of January and the first three weeks of February we use put options that expire at the end of the third week in April[7]. Similarly, for the last week of February and the first three weeks of March we use the puts that expire in May. This way, the impact

[7] All put options considered in this paper expire at the end of the third week of the respective month.

of duration is limited to at most one month as the remaining time to maturity varies from three to two months. As an alternative to this monthly roll-over, we also test an "on-the-run" series with a quarterly roll-over whose remaining time to maturity varies from six to three months. The put options used expire in the months March, June, September and December of each year. It turns out that the results are very similar but that the liquidity of the four mentioned months is far higher than some other months like, for example, February. Therefore, from now on, we only present the results based on the quarterly roll as we deem illiquidity to be potentially more harmful than an increased duration span.

5.2 Is there Cross-sectional Variation in perceived Exposures to Tail (market crash) Risk?

We estimate regression (5) at the bank level and obtain the bank-specific coefficients. To prevent that our results are driven by a few large outliers in the independent variables, we winsorize the independent variables at the 2.5% level. Figure 2 plots the individual gammas against bank size.

- Insert FIGURE 2 about here -

Figure 2 shows that there is a considerable cross-sectional variation among the individual gammas given that the median standard deviation is around seven and only a few small outliers exist. Therefore, it seems indeed to be the case that banks react differently to news about tail risk. Moreover, the plot does not reveal a clear pattern based on size so that a relationship between gammas and size does not seem to exist. Taken together, this information about the cross-sectional dispersion and in particular about the heavily exposed banks (as perceived by the market) may be helpful information for a regulator. It could facilitate the identification of potentially exposed banks already in good times so that preemptive, corrective actions may come at lower costs and less uncertainty.

5.3 Is the obtained information different from information contained in other measures?

5.3.1 Gamma vs. Beta

Given that a considerable cross-sectional variation of tail risk exposure exists, the question arises whether this information about tail risk exposure is also captured by other existing concepts. Our new gamma method will only add potential value if the information obtained is not already contained in other existing measures.

As a first step, in Figure 3 we plot the gammas against the betas that were obtained in the same regression. The scatter plot reveals a negative correlation between these two concepts, which has several interesting implications. First, the gammas do not contain the same information about bank risk as the betas do, so that the gammas could contain additional useful information. At this point let us note that in theory it could be possible that the conventional CAPM betas already included the information about tail risk exposure and that our proposal merely splits the conventional betas into a normal times risk part (the "new" beta in our regression) and a tail risk part (the gamma). This possibility is, however, not supported by our data. Estimating the beta alone and with the put options included does not make a large difference and the correlation among both betas is close to one. Moreover, both variables are negatively correlated with the gamma estimates. Note, that even if our method only split up the conventional CAPM beta, our method would still have the advantage of disentangling the two effects and making the tail risk exposure visible, which can be useful information to a regulator.

- Insert FIGURE 3 about here -

A second implication is that there seems to be a trade-off between taking on normal times risk (a higher beta) and taking on tail risk (a higher gamma). The figure suggests that banks hardly do both at the same time. This in turn implies that a regulator should not just look at the beta of a bank but, more importantly, she should pay more attention to the gamma of a bank as this represents the exposure to market crashes. For financial stability concerns a regulator might care much more about systemic risk (stemming, for example, from a market crash) than about an individual bank failure in normal times. In addition, it implies that other measures that simulate exposure to a market crash through the beta coefficient may be misleading, because they linearly impose the normal times risk exposure to the tail risk states. Our analysis suggests, that this might be a very crude approximation. Lastly, let us note that gamma and beta are likely to be determined together through a bank's business strategy. For this reason, it does not make sense to regress one on the other to investigate potential causalities. Moreover, in order to estimate gamma correctly, one needs to include beta in the regression as well, otherwise gamma will also capture some beta effects.

5.3.2 Gamma vs. Quantile-Beta

The preceding subsection has shown that the gammas contain different information that the betas. However, this result could simply stem from the fact that the two concepts have a different focus (normal times risk vs. tail risk). Therefore, we also need to compare the gammas to a concept that measures tail risk explicitly. In this section we will focus on the concept of quantile-betas. We calculate quantile-betas by using the well-known CAPM beta concept but instead of running an OLS regression we estimate the beta through a quantile regression (see for example Koenker and Basset (1978) and Koenker and Hallock (2001)) at very low quantiles, which should represent tail risk scenarios.

To understand the differences in the informational content better, we plot the quantile-betas against the gammas as well as the betas. Figures 4 and 5 show the plots against the quantile-betas obtained at the 5^{th} quantile. The plot of the CAPM betas against the quantile-betas in Figure 4 shows that their informational content is very similar as the two variables are highly correlated. In this context, it is not surprising that the gammas in Figure 5 are negatively correlated to the 5% quantile-betas, which implies that their informational content differs from the 5% quantile-betas.

- Insert FIGURES 4 and 5 about here -

At this point one has to keep in mind that the 5^{th} quantile does not represent real tail risk as the probability of such a market decline happening is about one in twenty business days, that is, once a month. For this reason, we repeat the exercise at the 1^{st} quantile but the results (not shown here) do not change significantly. Only when we move to the 0.1^{th} quantile (that is 0.1%) the informational content of the quantile-betas differs from the CAPM betas, as shown in Figure 6. In this plot a clear correlation between the two variables can no longer be visually detected. Intuitively, this development makes sense as we move from a market decline that happens on average once a month to one that happens on average once in four years (once in 1000 business days).

- Insert FIGURE 6 about here -

Increasing the severity of tail risk implies that we move to narrower information set, which is more likely to differ from the broader normal times information set. This in turn implies that we now have a competing tail risk measure which we have to compare our gammas with. Figure 7 plots the 0.1% quantile-betas against the gammas.

- Insert FIGURE 7 about here -

The plot reveals that the two variables still do not seem to be correlated. Although both concepts represent tail risk events, there seems to remain an informational difference between the two. One possible interpretation could be that the quantile-betas are backward-looking in the sense that they are based on actual past realizations whereas the gammas are more forward-looking as they represent market expectations through the share prices and, more importantly, through the option prices. Therefore, the forward-looking market perception / expectation of tail risk exposures could be a useful informational addition in the regulatory process as already discussed above.

5.4 Which banking activities are related to a bank's tail risk exposure?

In this section we address the issue of which banking activities are related to a higher tail risk exposure. This could be done in a straightforward two step method. In the first step the bank-specific gammas are estimated while in the second step the bank-specific gammas are regressed upon a number of balance sheet variables that represent the various banking activities. Although this two step method has the advantage of being simple and easy to interpret, it also has two potential disadvantages. First, there may exist the problem of generated regressors (Pagan, 1984) and second, the estimation is not efficient as information from the first step (estimating the gammas) is not used in the second step.

For these reasons, we develop a method which allows us to (efficiently) estimate the relationship in one step[8]. To capture the potential relationship between a certain balance sheet variable X and the tail risk sensitivity (proxied by changes in the adjusted put option), we add an interaction term of the two in equation (5). Since this interaction effect could be potentially non-linear in the activity, that is, more sensitive for banks with a very high (or very low) activity, we express X relative to its sample mean ($\tilde{X}$). We also interact the S&P 500 return with the balance sheet variable X to properly disentangle the effect of X on the sensitivities, as shown in equation (6) below:

$$\frac{dY}{Y} = \alpha + (\beta + \theta(X_i - \tilde{X}))\frac{dX}{X} - (\gamma + \delta(X_i - \tilde{X}))\frac{dP}{P + \overline{x}} + \varepsilon. \tag{6}$$

A bank's tail risk exposure is now measured by $\gamma + \delta(X_i - \tilde{X})$ instead of gamma alone. However, to determine the relationship between the tail risk exposure and the balance sheet variable X, one needs to differentiate with respect to X_i, which yields δ. Since we want to test various activities together, we employ a multivariate setting of equation (6):

$$\frac{dY}{Y} = \alpha + (\beta + \sum \theta_j(X_{ij} - \tilde{X}_j))\frac{dX}{X} - (\gamma + \sum \delta_j(X_{ij} - \tilde{X}_j))\frac{dP}{P + \overline{x}} + \varepsilon, \tag{7}$$

where i represents the individual bank and j the respective balance sheet variable.

Table 1 presents the δ coefficients from a set of regressions that are based on equation (7). The first column only contains the basic balance sheet characteristics. Only size (measured by the log of total assets), the loan-to-asset ratio and the leverage ratio (measured by the debt-to-asset ratio) are included. Size seems to be negatively related to tail risk exposure, which may be interpreted as the market's perception of large banks being too big to fail (TBTF). Anecdotal evidence seems to support this finding, because up until

[8] We also tested the two step version and it turns out that the results are very similar.

September 2009 it was mostly small banks that truly failed while several large banks got bailed out. The case of Lehman Brothers is an exception but the Lehman failure is not directly captured by our analysis since investment banks are not included in our sample. Moreover, it is (most likely) also not captured indirectly (for example through a change in perception) as our sample period ends at September 26, 2008 so that the period after the Lehman failure may be too short to materialize in the results. The loan-to-asset ratio is also negatively related to a bank's tail risk exposure. This finding is in line with other recent findings like, for example, DeJonghe (2008) or Demirguc-Kunt and Huizinga (2009) who both find that traditional banking activities are less risky compared to non-traditional activities. The last variable considered is the leverage ratio. Although a higher leverage ratio is often associated with more default risk, the absolute level does not come out significant in column one. There seem to be more subtle factors at work to which we return later in column seven.

Column two zooms in on the loan activities of a bank and includes some proxies for the loan quality and the return. Among the loan quality proxies only the loan growth variable is significant. A bank with a faster loan growth typically experiences a decline in loan quality and although overall, loans are seen to be less risky, a rapid loan growth is associated with higher tail risk exposure. Having corrected for the loan quality, it does not come at a surprise that a higher interest rate on the loans is associated with less tail risk. To rule out the possibility that the interest rate on the loans is a general proxy for return on assets, we also include this variable in column two. This however, poses the potential problem that the interest rate on the loans and the return on assets are correlated. We control for this by orthogonalizing the return on assets with the interest rate on loans and use the residuals as an estimate of the return of other (remaining) assets (ROOA). This ROOA captures especially the returns from non-traditional asset activities so that its positive relationship with tail risk exposure is again in line with other recent findings like, for example, Demirguc-Kunt and Huizinga (2009).

Next, we have a look at the major assets components of a bank. In column three we include held-to-maturity securities, for-sale securities and trading assets (all scaled by total assets) to the existing leverage ratio, size and loan-to-assets ratio. As a result, only the trading assets are slightly significant and the loan-to-assets ratio turns insignificant, while the other asset items are insignificant, too. At this point, one has to keep in mind that, even when you control for size, the traditional and the non-traditional activities are likely to be negatively correlated due to the business strategy of a bank. This introduces the issue of multicollinearity, which is likely to affect the estimates. Therefore, in column four we use the ratio of commercial and industrial loans to total assets (C&I Loans/TA) as proxy for the loan-to-asset ratio (the traditional activity) as it is less correlated with the non-traditional activities. The result is that especially the trading assets and the for-sale securities are contributing to tail risk. Held-to-maturity securities have a positive coefficient as well, but its magnitude and significance is lower. The C&I-loans-to-asset ratio is insignificant similar to the loan-to-asset ratio in column three.

It has often been argued (also by us) that non-traditional banking activities contribute to (tail) risk exposure. In columns five and six, we will test, which role financial innovations play among the non-traditonal activities. First, we investigate securitization and asset sales activities. In addition to the total value of securitization and asset sales (both scaled by total assets) we also include the internal and external credit exposure arising from these activities. The internal credit exposure arises from a bank's own securitization or asset sale activities via recourse and other credit enhancing agreements between the bank and its special purpose vehicle (SPV). An external credit exposure can arise if a bank provides any kind of credit enhancements to other banks' securitization structures.

Column five shows that only the external credit exposure variable is significant with a positive sign. This is in line with what theory would predict as external credit exposure is new credit exposure taken on in addition to the own existing credit exposure. Moreover, the credit exposure of these securitization structures should only materialize in cases of a severe market crash, making it a clear contributor to tail risk. One way to explain the insignificance of a bank's own securitization and asset sale activities is that two opposing forces are at work. In its purest sense, securitization and asset sales are a mean of off-loading risk to other market participants, making a bank in principle less exposed to tail risk[9]. However, the recent experience has shown that these activities itself were a profitable income source so that banks were inclined to take on more risk with the prospect of selling it later. In addition, although the credit exposure legally disappeared from the balance sheet to the SPV (which is legally independent), the market might have expected that this strict legal separation may not survive a market crash for reputational concerns. As was the case with Bear Stearns, a bank might be forced to buy back the assets from the SPV to protect its reputation and customer base. Therefore, the credit exposure (which is mostly tail risk exposure) was not fully and credibly gone through the securitization.

Column six focuses on a financial innovation that is already a little older, namely derivatives. Based on the available data we can make the distinction between derivatives that are being held for trading purposes and derivatives that are being held for other purposes (most likely hedging). From a theoretical perspective one would expect that

[9] Under the assumption that a bank keeps the equity tranche (e.g. to align the monitoring incentives), it should still be exposed to normal times risk, as the equity tranche is the first to lose.

derivatives held for hedging reduce tail risk while the effect for derivatives trading is not that clear cut. As long as a bank always finds a counterparty its risk exposure should be small but given that this is not always possible, a bank may actually increase its tail risk exposure. The results in column six show that especially derivatives held for trading do contribute to tail risk. However, the derivatives held not for trading are simply insignificant instead of negative and significant. There are two potential explanations for this observation. First, not all derivatives may be used for hedging or do not create a perfect hedge, which may hamper the effect. Second, there is still the exposure to counterparty risk , which typically only materializes in tail risk scenarios.

In column one we found that the leverage ratio is not contributing to tail risk exposure. To shed light on the question which activities on the liabilities side might do so, we include more detailed information on the share of deposits and the composition of deposits. In the last column of Table 1 we include the deposit-to-liabilities ratio and the ratio of time deposits above \$100.000 to domestic deposits in addition to the variables from column one. The reason why we focus on the time deposits above \$100.000 is that these deposits are typically not insured, which makes them very similar to wholesale funding as both types might be prone to a bank run. Due to the nature of the FR Y-9C reports we cannot obtain data for these deposits in foreign subsidiaries so that we focus on the domestic deposits[10]. A brief check of the data however revealed that more than 90% of the banks have less than 10% of deposits abroad so that the concentration on domestic deposits should not affect our findings too much. The results in column seven show that the leverage ratio is again not significant just like the deposit-to-liabilities ratio. However, controlling for these factors, one can see that the time deposits above \$100.000 do contribute to tail risk. To the extent that these deposits are similar to wholesale funding, these results are similar to Demirgüç-Kunt and Huizinga (2009) who find that wholesale funding increases bank risk[11].

6 Conclusion

Conclusion

[10] The FR Y-9C reports (which report the activities at the Bank Holding (i.e. the group) level) are in general less detailed about the asset and liabilities activities than, for example, the Call Reports (which is the equivalent at the commercial bank level). This is also the reason why we cannot use more detailed information on other liabilities which are not deposits in their nature. However, as said before, we have to rely on the BHC information as it is the BHC that is listed.

[11] Note, that Demirgüç-Kunt and Huizinga do not distinguish between normal times risk and tail risk but rather look at the Z-score.

TO BE WORKED OUT

- We propose a forward looking way to measure tail risk (market crash) exposures at banks

- Our method is easy to calculate and only requires market data

  $\Rightarrow$ available on a daily basis

- The observation of an actual crash is not needed to identify a bank's exposure

- We estimate exposures at individual bank level $\Rightarrow$ the gammas contain different information than betas and quantile-betas

- Moreover, we test the relation between individual exposures and asset and liability activities and find that non-traditional activities contribute more to tail risk exposure

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Tables

Table 1: Coefficients of the Interaction Terms Balance Sheet Variables ⟷ Put Option

Dep.Var.: Daily Stock Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Debt/TA	0.727	36.53	-21.45	-19.68	2.117	-6.373	-3.771
	(29.25)	(30.54)	(33.01)	(30.79)	(30.08)	(29.85)	(29.97)
log(TA)	-2.722***	-2.934***	-2.681***	-2.708***	-2.530***	-3.237***	-2.571***
	(0.371)	(0.384)	(0.541)	(0.492)	(0.415)	(0.476)	(0.427)
Loans/TA	-23.12***	-13.08***	2.485		-23.02***	-21.28***	-23.16***
	(4.433)	(4.128)	(18.17)		(4.440)	(4.637)	(4.785)
Non-Performing Loans/TL		-106.3					
		(75.26)					
Loan Loss Allowance/TL		348.2					
		(225.6)					
Loan Growth		19.10**					
		(9.178)					
Interest Loans/TL		-285.9***					
		(29.95)					
ROOA		569.3***					
		(57.88)					
Held-to-Maturity Securities/TA			25.62	23.33*			
			(23.37)	(13.38)			
For-Sale Securities/TA			31.25	28.64***			
			(21.01)	(6.360)			
Trading Assets/TA			66.68*	63.06***			
			(34.97)	(20.20)			
C&I Loans/TA				-0.0419			
				(7.882)			
Total Securitization/TA					-3.396		
					(6.303)		
Loans Sold/TA					-48.42		
					(41.47)		
ICE (Sec+Sales)/(Sec+Sales)					0.953		
					(1.486)		
ECE (Sec+Sales)/TA					147.4**		
					(64.64)		
Derivatives held for trading/TA						0.361***	
						(0.108)	
Derivatives not for trading/TA						3.092	
						(3.605)	
Time Dep.>100'/Domestic Dep.							10.44**
							(4.746)
Deposits/Liabilities							3.889
							(7.265)
Observations	154242	154242	154242	154242	154242	154242	154242
R^2	0.230	0.239	0.230	0.230	0.230	0.230	0.230

TA=Total Assets; TL=Total Loans; ROOA=Return of other Assets; ICE=Internal Credit Exposure

ECE=External Credit Exposure; Dep.=Deposits

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Figures

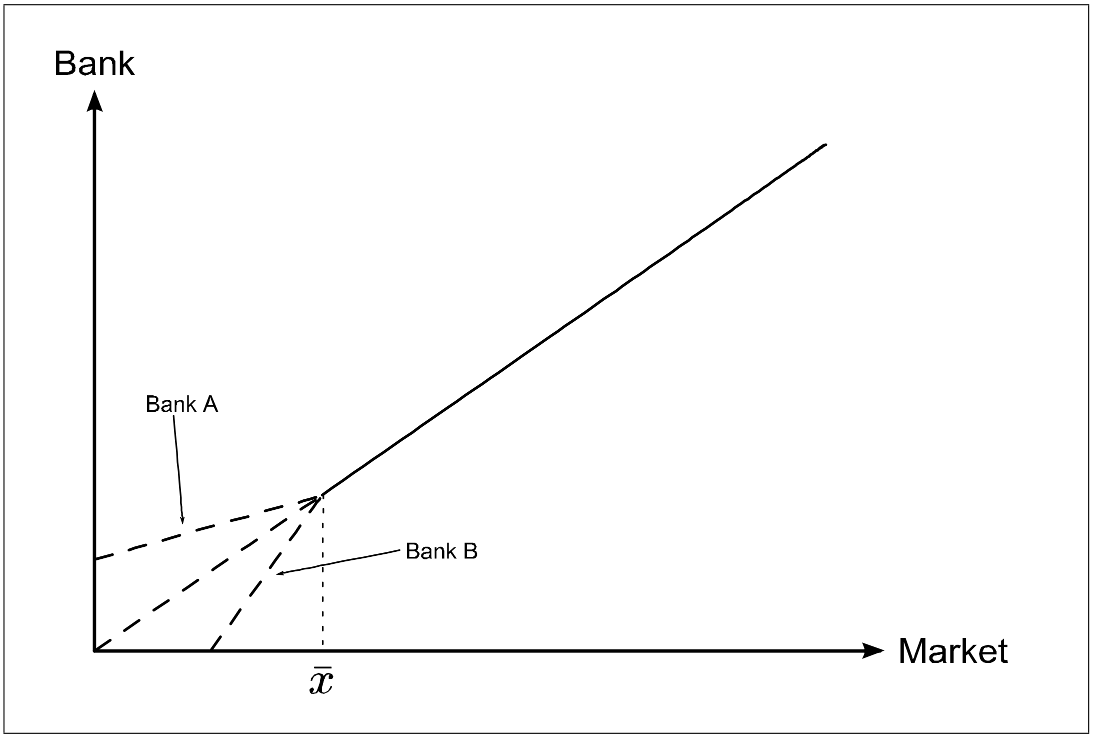

Figure 1: Relationship of Bank and Market Values

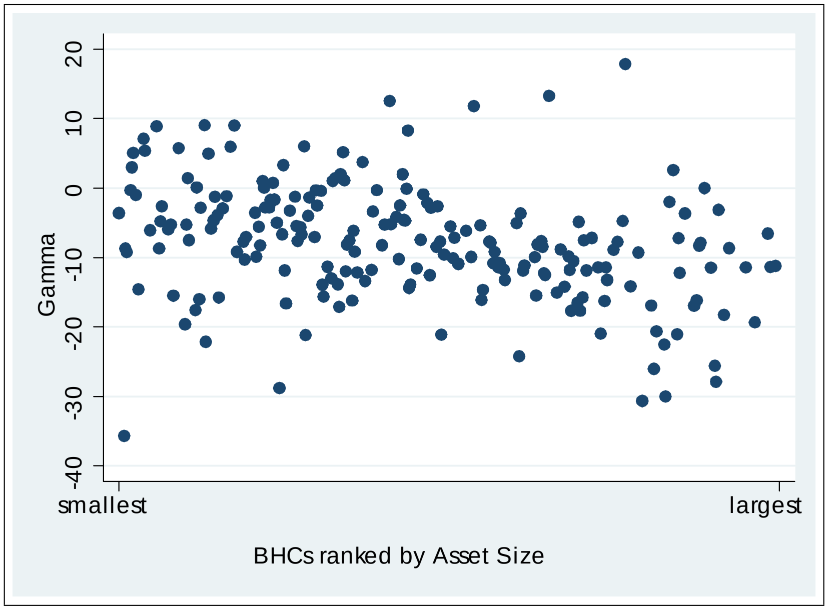

Figure 2: Individual Gammas plotted against Bank Size

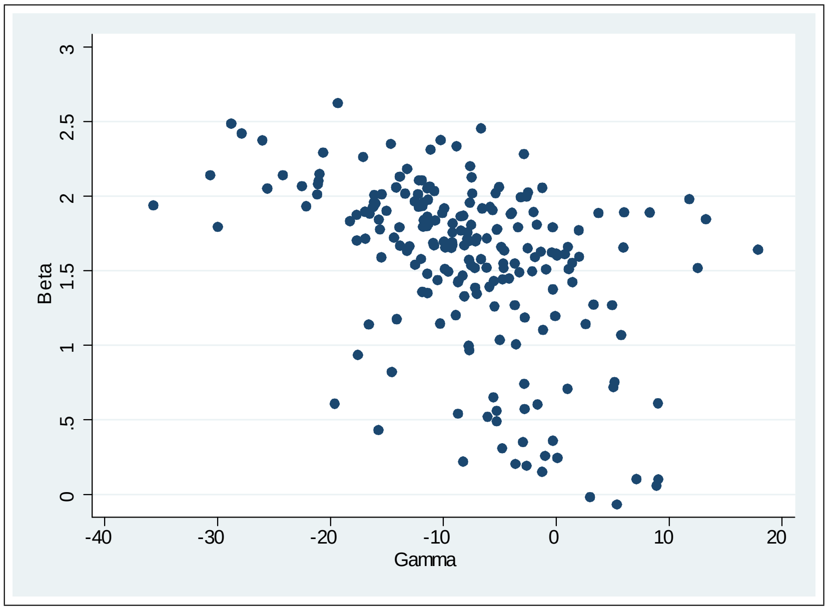

Figure 3: Individual Gammas plotted against Individual Betas

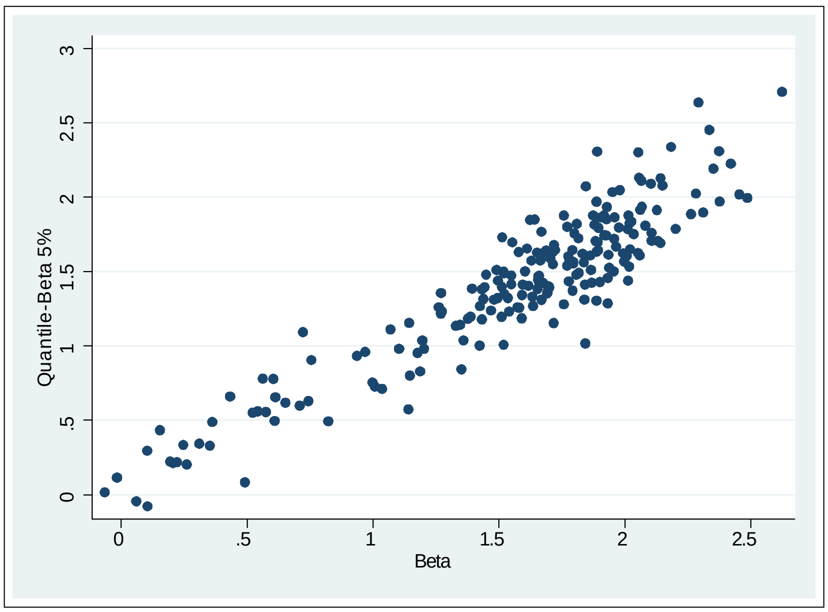

Figure 4: Individual Betas plotted against Individual Quantile-Betas (5% Quantile)

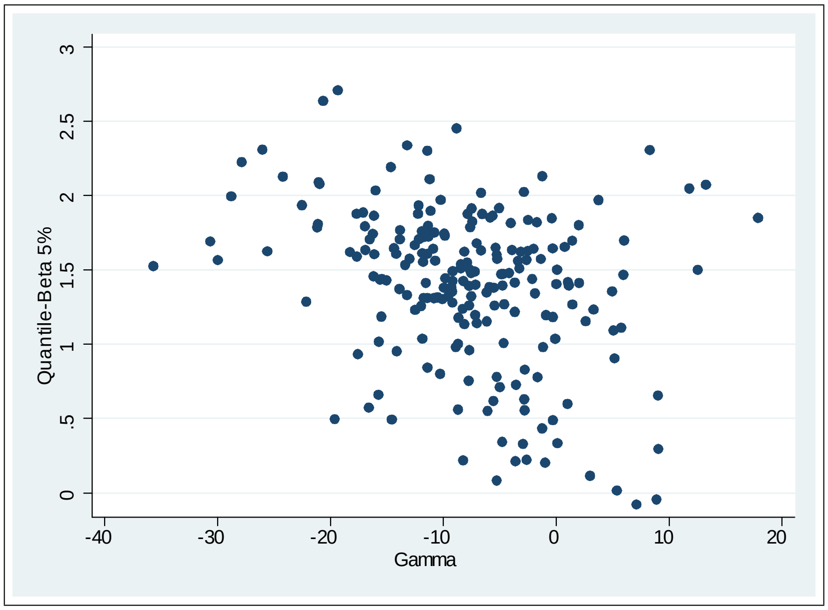

Figure 5: Individual Gammas plotted against Individual Quantile-Betas (5% Quantile)

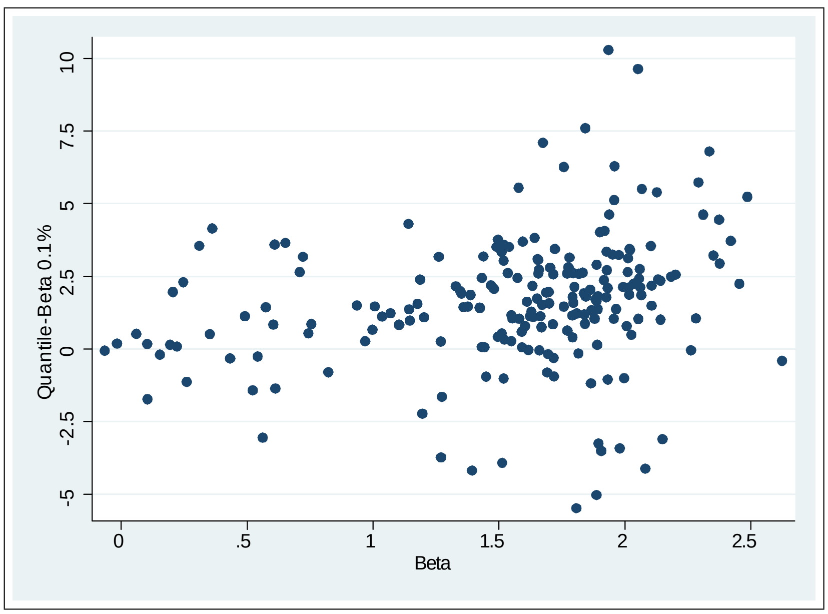

Figure 6: Individual Betas plotted against Individual Quantile-Betas (0.1% Quantile)

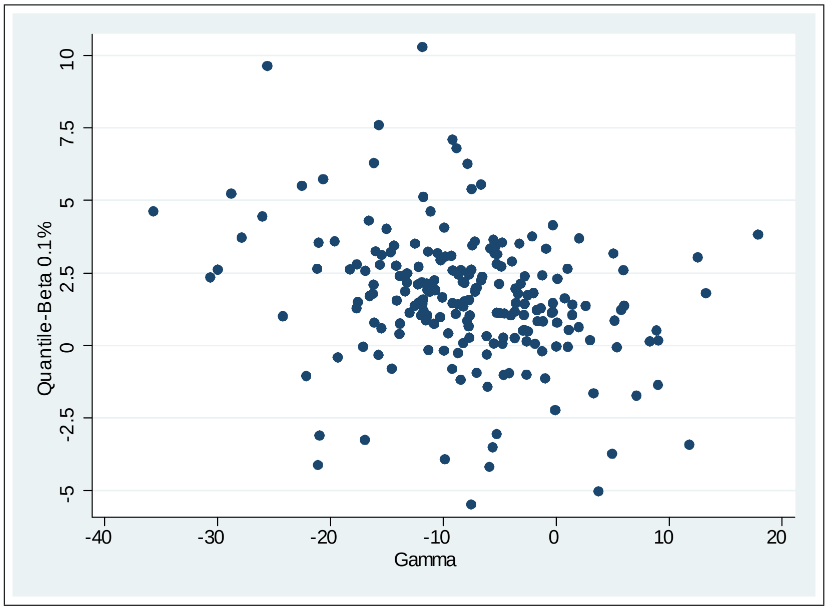

Figure 7: Individual Gammas plotted against Individual Quantile-Betas (0.1% Quantile)