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# Measuring the Tail Risks of Banks

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# Measuring the Tail Risks of Banks<sup>\*</sup>

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## Abstract

In order to address the risk of systemic crises it is of paramount importance to have advance information about banks' exposures to large (negative) shocks. In this paper we develop a simple method for quantifying such exposures in a forward-looking manner. The method is based on estimating banks' share prices sensitivities to (market) put options and does not require the actual observation of tail risk events. Interestingly, we find that estimated tail risk exposures for U.S. Bank Holding Companies are negatively correlated with their share price beta, suggesting that banks which appear safer in normal periods are actually more crisis prone. We also study the determinants of banks' tail risk exposures and find that their key drivers are uninsured deposits and non-traditional activities that leave assets on banks' balance sheets.

JEL classification: G21, G28

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## 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 induce large costs for the economy. The task of supervisors and regulators is to avoid and mitigate, as far as possible, such crises. For this they need advance information about how banks are exposed to shocks to the economy. This allows them to identify weak banks and put them under increased scrutiny but also to monitor general risks in the financial system. When evaluating the exposure of banks it is also of paramount importance to distinguish between exposures to normal market shocks, and exposures to large shocks. For example, a financial institution that follows a tail risk strategy (such as writing protection in the CDS market) may appear relatively safe in normal periods as it earns steady returns but may actually be very vulnerable to significant downturns in the economy.

Currently, supervisors and regulators obtain their information to a large extent from information generated by the bank itself, such as its accounts. While these sources are a crucial ingredient of the evaluation process they are not free from drawbacks. For example, most of this information is under the discretion of banks and may be used strategically<sup>1</sup>. Moreover, this data is typically backward looking and available only at relatively low frequency. Accounting information also misses important aspects such as informal knowledge (e.g., CEO reputation) or information contained in analysts' reports.

In recent years there has been growing interest in using market-based measures of bank risk. This is on the back of evidence that market signals contain valuable information about banks' risks (see Flannery (1998) and Flannery (2001) for surveys). While some of these measures focus on individual bank risk (such as Moody's KMV), others explicitly take into account the systemic aspect (e.g., Hartmann et al. (2006), Straetmans et al. (2008), De Jonghe (2009) and Adrian and Brunnermeier (2009)). These methods have in common that they essentially use information from historical tail risk events to compute *realized* tail risk exposures over a certain period.

This paper differs from these approaches in that we develop a forward-looking measure of bank tail risk. We define a bank's (systemic) tail risk as its exposure to a large negative market shock. We measure this exposure by estimating a bank's share price sensitivity to changes in far out-of-the-money put options on the market, correcting for market movements themselves. As these options only pay out in very adverse scenarios, changes in their prices reflect changes in the perceived likelihood and severity of market crashes. Banks that show a high sensitivity to such put options are hence perceived by the market as being severely affected should such a crash materialize. As this sensitivity reflects perceived exposures to a hypothetical crash, it is truly forward-looking in nature. This property is important to the extent that bank risks change quickly and hence historical tail risk exposures become less informative. Another advantage of this method is that it does not require the actual observation of any crashes, as the method relies on changes in their perceived likelihood.

We use our methodology to estimate tail risk exposures of U.S. bank holding companies. We find that the estimated exposures are inversely related to their CAPM beta. This seems a very

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<sup>1</sup> For evidence on such strategic use see, for example, Wall and Koch (2000) and Hasan and Wall (2004) for the reporting of loan losses and Laeven and Majnoni (2003) for the provisioning of loan losses. Huizinga and Laeven (2009) also provide evidence that banks have used accounting discretion to overstate the value of their distressed assets in the current crisis.

interesting result with potentially important implications for financial regulation as it suggests that banks that appear safe in normal periods actually tend to be the banks that are most exposed to crashes. This may be because such banks follow tail risk strategies. We also compare our measure to a common measure of bank tail risk: the tail risk beta, which is obtained through quantile regressions. We find that both measures are fairly uncorrelated and hence provide different information. A potential explanation for this lies in the backward-looking nature of the tail risk beta and the fact that its estimation relies on observing (rare) tail risk events.

We also use our methodology to characterize the main drivers of bank tail risk. Understanding these drivers is important for regulators as it gives them information about which activities should be encouraged and which not. There is so far very little research on this question (a notable exception is De Jonghe (2009)). Our main findings are that variables which proxy for traditional banking activities (such as lending) are associated with lower perceived tail risk. Several non-traditional activities, on the other hand, are perceived to contribute to tail risk. In particular, we find securities held for-sale, trading assets and derivatives used for trading purposes are associated with higher tail risk. These findings are consistent with observed experience in the current crisis. Interestingly, securitization, asset sales and derivatives used for hedging are not associated with an increase in tail risk exposure. This indicates that a transfer of risk itself is not detrimental for tail risk, but that non-traditional activities that leave risk on the balance sheet are. On the liability side we find that leverage itself is not related to tail risk but that large time deposits (which are typically uninsured) are. We also find that perceived tail risk falls with size, which is indicative of bail-out expectations due to too-big-to-fail policies.

The remainder of this paper is structured as follows. In Section 2 we briefly review existing measures of tail risk. Section 3 develops the methodology for measuring tail risk exposure using put option sensitivities. Section 4 presents the empirical analysis. Section 5 concludes.

## Existing Tail Risk Measures

The Value-at-Risk (VaR) has for many years been the standard measure used for risk management. VaR is defined as the worst loss over a given holding period within a fixed confidence level<sup>2</sup>. A shortcoming of the VaR is that it disregards any loss beyond the VaR level. The expected shortfall (ES) is an alternative risk measure that addresses this issue. The ES is defined as the expected loss conditional on the losses being beyond the VaR level. Another frequently used 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

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<sup>2</sup>See Standard & Poors (2005) for a brief overview and Jorion (2006) for a more detailed approach.

the fraction of those firms in previous years, which had the same distance to default and actually defaulted within one year.<sup>3</sup>

While these measures focus on the bank in isolation, there has been a growing interest in recent years in systemic measures of bank risk. One strand of the literature focuses on tail-betas (see Hartmann et al. (2006), Straetmans et al. (2008) and De Jonghe (2009)). This concept applies extreme value theory to derive predictions about an individual bank's value in the event of a very large (negative) systematic shock. Loosely speaking, this method uses information from days where stock market prices have fallen heavily and considers the covariation with a bank's share price on the same day. It thus measures realized covariances conditional on large share price drops. A difficulty encountered when applying this method is that tail risk observations are rarely observed, and hence a large number of observations are needed to get accurate estimates (De Jonghe (2009) suggests at least six years of daily data).

Acharya et al (2008) develop a measure similar to the concept of market dependence, which is based on expected shortfalls instead of betas. They propose measuring the Marginal Expected Shortfall (MES), which is defined as the average loss by an institution when the market is in its left tail. Adrian and Brunnermeier (2009) consider a different aspect of systemic risk. They estimate 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 bank'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. An advantage of the CoVaR is that it is relatively simple to estimate, as it is based on quantile regressions. In terms of its informational properties it is similar to the tail risk beta in that it measures realized tail risk.

Our measure is most similar to the tail risk betas as we also measure bank exposures to large market swings. A difference that is important for the interpretation of the estimates, however, is that while the tail risk beta relates to large daily market drops, we estimate exposures to a large prolonged downturn in the market (e.g., 3 to 6 months).

## Measuring Tail Risk Using Put Options Sensitivities

In this section we present our methodology for measuring banks' tail risk exposures. We define the latter to be the bank's exposure to a general market crash (that is, a severe downturn in the economy). If the market crashes, a bank may suffer large, simultaneous losses on its assets, which may push it close to or into bankruptcy. Crucially, the extent to which it is exposed to crashes may differ from its normal market sensitivity. Consider two banks, A and B. Bank A invests mostly in traditional banking assets such as, for example, loans to businesses and households. Moreover, it invests in assets that are mainly exposed to normal period risk, such as, for example, junior tranches of securitization products (which lose value for modest increases in defaults, but are insensitive to defaults that go beyond the first loss level). In addition to these assets, bank A insures itself against

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<sup>3</sup> (Subordinated) debt and CDS spreads are an alternative and attractive measure of a bank's default risk. A shortcoming of these measures is that these spreads are not available for many banks (in the case of CDS spreads) and often not very liquid (in the case of bonds).

default by buying protection on its assets (such as by buying credit default swaps on its loans). Bank A's equity value will thus move more with the market in normal periods than in times of crisis.

Bank B, by contrast, follows a different business strategy. It does have traditional assets such as, for example, loans. However, in addition, it also follows investment strategies that return a small and steady payoff in normal periods but incur catastrophic losses when the market crashes. Examples for this would be selling protection in the credit default swap (CDS) market or buying senior tranches of securitization products, which lose value only when all other tranches have already incurred a total loss. Thus, even though bank B's equity value may behave similarly to bank A's in normal periods, it tends to fall relatively more when the market crashes. This scenario is depicted in Figure 1, where bank A performs better in crash times (market values below  $\bar{x}$ ) than bank B, even though in normal periods equity values are similarly distributed.

- Insert FIGURE 1 about here -

We next describe our method for measuring a bank's tail risk exposure. For this suppose that there is a representative firm in the economy (which we interpret as the market). This firm exists for one period only and its (stochastic) next period equity value is denoted with  $x$ . Similarly, consider a bank with next period equity value  $y$ . We assume for the relationship between equity values of the bank and the market:

$$y(x) = \begin{cases} x^\beta & \text{if } x \geq \bar{x} \\ \frac{x^\beta}{\left(\frac{\bar{x}-x}{\bar{x}}+1\right)^\gamma} & \text{if } x < \bar{x} \end{cases} \quad (1)$$

When  $x \geq \bar{x}$ , the bank's equity value is thus identically distributed to that of a firm with a beta of  $\beta$ . However, for  $x < \bar{x}$ , the bank's equity value additionally depends on the relative shortfall of the market to  $\bar{x}$ ,  $\frac{\bar{x}-x}{\bar{x}} \in [0,1]$ . For  $\gamma > 0$  its equity value will be more sensitive to the market, hence the bank has tail risk over and above the normal period exposure, while for  $\gamma < 0$  we have the opposite case. Only in the case of  $\gamma = 0$  does the bank's tail not differ from its normal period risk.

Since tail risk realizations ( $x < \bar{x}$ ) are rarely observed, our estimation relies on changes in perceived tail risk, which we will measure through changes in put options prices. For this consider a put option with strike price  $\bar{x}$  that is deep out-of-the-money ( $\bar{x}$  is hence a tail risk realization). We have for the pay-off from this put

$$p(x) = \begin{cases} 0 & \text{if } x \geq \bar{x} \\ \bar{x} - x & \text{if } x < \bar{x} \end{cases} \quad (2)$$

Inserting into (1), totally differentiating wrt.  $y$  and dividing by  $y$  yields

$$\frac{dy(x)}{y} = \beta \frac{dx}{x} - \gamma \frac{dp}{p+\bar{x}}. \quad (3)$$

Percentage changes in the bank's equity values  $\left(\frac{dy(x)}{y}\right)$  are thus explained by percentage changes in the market  $\left(\frac{dx}{x}\right)$ , giving the standard  $\beta$ -effect. Additionally, they are also explained by relative changes in the value of the option,  $\left(\frac{dp}{p+\bar{x}}\right)$ <sup>4</sup>, arising from tail risk exposure.

In our empirical implementation we thus identify tail risk sensitivities by adding a put option (on the market) to a standard market regression and interpreting the sign of the put option coefficient. Tail risk sensitivities will thus be identified by changes in put option prices (that is, changes in expected market crash likelihood and severity).<sup>5</sup>

## A Discussion of the Methodology

We believe that our methodology has several attractive features. First, the method is forward-looking in nature, that is, it captures *expected* tail risk exposure at banks. This contrasts with other popular methods for measuring tail risk, such as tail risk betas or the CoVAR. These methods essentially compute correlations (or covariation) of banks with the market (or other banks) at days of large share price drops. They thus draw inferences from historical tail risk distributions and hence measure realized tail risk. The difference between forward and backward-looking measures is likely to be limited when banks only undergo small changes in their risks over time, but is potentially important in a dynamically evolving financial system.

Second, our measure identifies banks' tail risk exposure through *changes in expected* market tail risk, as measured by put option prices. This has the advantage that for our estimation we do not need tail risk events to actually materialize. Such events, by definition, occur only very infrequently and hence it is difficult to estimate their properties. Existing measures that rely on the historical distribution of tail risk events reduce this problem by relying on a large time series and by looking at modest tail risk realizations that occur more frequently. Our method allows the measurement of exposure to extreme forms of tail risk (for this one simply includes a very far out-of-the-money put option) and we can also estimate tail risk exposures using relatively short horizons.<sup>6</sup>

Since we measure exposures to market crashes, our measure captures *systemic* tail risk exposure. This is desirable since externalities from banking failures are typically associated with systemic crises, and not isolated bank failures. It should, however, be kept in mind that a bank that

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<sup>4</sup> The correct term here is indeed  $\left(\frac{dp}{p+\bar{x}}\right)$  and not, as one might think,  $\left(\frac{dp}{p}\right)$ . The bank-market relationship consistent with  $\left(\frac{dp}{p}\right)$  would be  $y = \frac{x^\beta}{(\bar{x}-x)^\gamma}$  for  $x < \bar{x}$  as one can easily verify, which is not a sensible one as for  $x = \bar{x}$  the denominator would then be infinite. Intuitively, the reason we need to correct for  $\bar{x}$  is that otherwise for a put option with a low  $p$ , small changes in tail risk would translate into large *relative* put option changes.

<sup>5</sup> The estimation of  $\gamma$  is akin to estimating the factor-loadings in the asset pricing literature (see, for instance, Ang et al. (2006) and the references therein). While in the asset pricing literature the factor loadings are used in a second step to predict returns, we are interested here in the cross-sectional distribution of the factor-loadings. More precisely, we propose using the cross-sectional variation to identify banks that are perceived as being prone to a market crash.

<sup>6</sup> Another attractive feature of our measure is that it is very easy to compute, as one simply has to run a market regression amended for a (market) put option.

has a low estimated systematic tail risk may still be individually very risky to the extent that it pursues activities that are uncorrelated with the market. Finally, it should be noted that our measure, as other market-based measures, is net of any bailout expectations. If, for example, markets anticipate that governments may bail out certain banks, for example because they are too-big-to-fail, then these banks may have a low perceived tail risk, even if their underlying activities are relatively risky.

## Empirical Analysis

### Data

We collect daily data on banks' share prices and the S&P 500 (our proxy for the market) for the period October 4<sup>th</sup> 2005 until September 26<sup>th</sup> 2008 via Datastream. Put option data on the S&P 500 (more details will follow below) for the same period is from IVolatility.<sup>7</sup>

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. We focus on the BHC instead of the commercial bank itself, as 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 mitigate illiquidity issues. Foreign banks (even when listed in the U.S.) and pure investment banks are also excluded. The final sample contains 209 Bank Holding Companies.

An important question is the choice of the option strike price. Ideally we would choose options such that on each day they represent the same crash probability. Taking an option with the same strike price each day is hence not desirable, as market prices change over time and an initially out-of-the-money option may become an in-the-money option (this is precisely what would have happened over our sample period). Taking the strike price to be a (fixed) fraction of the S&P500 is also not a good solution as this ignores that the likelihood of tail risk realizations is also driven by the volatility. We hence decided to choose options such that their price does not vary over time, that is we adjust the option's strike price each day such that its (previous day) price stays the same. For this we use an option price of 0.5 (50 cents), which translates into an implied strike that was on average 33% below the S&P 500 during our sample period<sup>8</sup>.

In order to compute the option price change for, say day 1, we proceed as follows. We first identify among all traded options the strike prices that give day 0 prices closest to 0.5. We then calculate the weight that makes their average price 0.5. Given this weight, we calculate the weighted average of their prices at day 1 and calculate from this the change of the price,  $dP$ , from day 0 to day

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<sup>7</sup> We also considered using put options on a banking index (the BKX index) instead of the market. There are two major disadvantages to this. First, the banking sector index in itself will already reflect tail risk in the financial system, thus the interpretation of the  $\gamma$ -estimates is not straightforward. Second, put option prices on the index are fairly illiquid.

<sup>8</sup> In the more tranquil (low volatility) times of 2006, the average implied strike was still around 28% below the S&P 500 while after June 2007 it was on average around 38% below the S&P 500.



1. We thus compute price changes of options whose (hypothetical) strike price varies from day to day.

We initially considered all out-of-the-money puts. A first inspection, however, revealed that the 100er strikes (i.e. 500, 600, 700 etc.) are much more liquid than put options with other strike prices. We therefore use only these puts. For each day an option's strike price and its price change are then calculated according to the procedure described above. In order to mitigate the influence of changes in the remaining time to maturity on our analysis, we use for this an "on-the-run" series, where each quarter we jump to a more recently issued option with longer maturity. As a result, the remaining time to maturity is limited to an interval of between three and six months.

### Estimated Tail Risk Exposures

We estimate equation (3) for each bank. For this the independent variable is winsorized at the 2.5% level. Figure 2 shows the obtained tail risk estimates (gammas) plotted against bank size. It can be seen that there is considerable variation among the bank's gammas. There also seems to be a pattern of large banks having lower tail risk.

- Insert FIGURE 2 about here -

An important first question is whether our tail risk measure really adds anything in terms of informational content to the normal beta. For example, it may simply be that banks with large tail risk also have large beta. In this case, estimating the tail risk beta separately is of little value. Figure 3 plots banks' gammas against betas. The scatter plot shows that this concern is not justified. In fact, there is a strong negative relationship between beta and gamma. This suggests that the banks that appear safe if judged by their beta, are actually the ones that have a high tail risk.

- Insert FIGURE 3 about here -

What can explain this negative correlation between normal period and tail risk? One explanation is so-called tail risk strategies, which produce steady returns in normal periods but actually expose the banks to severe downturns. For example, an institution that writes protection in the CDS market receives in normal periods a steady stream of insurance premia. However, in a significant recession many exposures will simultaneously default and large losses may materialize. Many trading strategies, such as the ones exploiting apparent arbitrage relations, create similar pay-off distributions. Another explanation for this negative correlation is that highly profitable institutions that operate in risky environments protect their franchise, for example by buying protection in the CDS market or by imposing a less fragile capital structure.

We are also interested in how our measure of tail risk relates to other measures of tail risk. An easy to implement measure is quantile-betas, which are obtained by running quantile regressions for an otherwise standard beta equation (see for example Koenker and Basset (1978) and Koenker and Hallock (2001)). In our context, we are of course interested in the lower quantiles in such a regression.

Figure 4a shows estimated quantile-betas obtained at the 5<sup>th</sup> quantile plotted against our gamma. A negative relationship is detectable, which is surprising. However, it can be explained by

considering Figure 4b, which plots the quantile-betas against normal betas. We can see that there is a very strong positive relationship. The likely cause is that the 5<sup>th</sup> quantile does not represent sufficiently extreme risk and hence may not differ that much from normal period risk. And since we already know that normal beta and gamma are negatively correlated, this explains the direction of the relationship in Figure 4a.

- Insert FIGURES 4a and 4b about here -

We repeat the exercise at the 1<sup>st</sup> quantile but the results (not reported here) are similar. Only when we move to the 0.1<sup>th</sup> quantile (that is 0.1% of the distribution) does the informational content of the quantile-betas differ from the CAPM betas. Figures 5a and 5b show the results. Figure 5a shows that there is no longer a negative relationship between our gamma and the quantile beta, and Figure 5b shows that there is also no longer a relationship with the standard beta.

- Insert FIGURES 5a and 5b about here -

Even though a negative correlation between the two tail risk measures is now absent, it is still surprising that there is no positive relationship between these measures. They thus seem to pick up different information. One difference between the methods is obviously that one is backward - and the other forward-looking. More importantly, however, there is also a conceptual difference. The quantile regressions capture tail risk as measured by large *daily* price changes. In this respect, an institution has a large tail risk beta if it moves a lot on days where the market drops a lot. This is different from our gamma, which intends to capture the comovement in case the market crashes over a period of three to six months (the average maturity of our put options). Arguably, for financial stability considerations the latter information is more relevant as large daily market drops (which may occur for example in a boom) do not necessarily result in stability issues. By contrast, a prolonged market downturn is likely to cause substantial problems at banks.

This conceptual difference may explain why the correlation among the measures is low. Consider for example a financial institution that follows a tail risk strategy by writing protection in the CDS market. This bank will be vulnerable to a severe downturn in the economy, as discussed earlier, and will hence have a high estimated gamma. However, the institution will not be very sensitive to large daily share price fluctuations as long as the downturn has not set in. Hence, it may have a low quantile-beta.

### Determinants of Bank Tail Risk

In this section we are studying whether and how a bank's business activities relate to its tail risk. The most obvious way to do this is by regressing (estimated) gammas upon a number of balance sheet variables that represent various banking activities. This two step method has two disadvantages. First, it creates 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 employ a method which enables us to (efficiently) estimate the relationship in one step<sup>9</sup>. For this we amend equation (3) to allow a bank's put option sensitivity to vary with a certain bank activity, say  $B$ . Since this interaction effect could be potentially non-linear in the activity, we express  $B$  relative to its sample mean ( $\hat{B}$ ). In addition, we also interact the S&P 500 return with the balance sheet variable  $B$  to take into account that general market sensitivities may also differ depending on bank activities. We obtain the modified equation:

$$\frac{dy(x)}{y} = \alpha + \left(\beta + \theta(B - \hat{B})\right) \frac{dx}{x} - \left(\gamma + \delta(B - \hat{B})\right) \frac{dp}{p+\bar{x}}. \quad (4)$$

The coefficient  $\delta$  in this equation gives us the relationship between a bank's gamma and activity  $B$  (the equivalent of the coefficient of a regression of estimated gammas on  $B$ ), evaluated at the mean. Since we are interested in several determinants of bank tail risk, we employ a multivariate variant of equation (4):

$$\frac{dy(x)}{y} = \alpha + \left(\beta + \sum \theta_j(B_j - \hat{B}_j)\right) \frac{dx}{x} - \left(\gamma + \sum \delta_j(B_j - \hat{B}_j)\right) \frac{dp}{p+\bar{x}}, \quad (5)$$

where  $j$  represents the respective balance sheet variable.

Table 1 presents the balance sheet coefficients  $\delta$  from a set of pooled regressions that are based on equation (5). The first column contains the results from a regression with some basic bank characteristics: size (measured by the log of total assets), the loan-to-asset ratio and the leverage ratio (measured by the debt-to-asset ratio). Size is negatively related to tail risk exposure. This may indicate that markets perceive large banks as being too-big-to-fail (TBTF). 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: both De Jonghe (2009) and Demircuc-Kunt and Huizinga (2009) find that traditional banking activities are less risky than non-traditional activities. The last variable considered is the leverage ratio. Although a higher leverage ratio is often associated with more default risk, it does not come out significant here (we return to this issue later).

Column two focuses on banks' lending activities by including proxies for loan quality and profitability. Among the loan quality proxies only the loan growth variable is significant, indicating a positive relationship with tail risk. This is consistent with the idea that a bank may only grow faster at the cost of lowering lending quality, and hence may become more exposed in a downturn<sup>10</sup>. We also find that a higher interest rate on the loans is associated with less tail risk, which can be explained by the fact that this indicates a higher profitability of banks, thus exposing it less to a crash in the market. Additionally, we include the return of assets (ROA) to capture the returns from other (partly non-traditional) asset activities. We find a positive relationship with tail risk, which is consistent with other recent findings (e.g., Demircuc-Kunt and Huizinga (2009))<sup>11</sup>.

Next, we turn to the influence of other assets. In column three we include held-to-maturity securities, for-sale securities and trading assets (all scaled by total assets). Only trading assets turn

<sup>9</sup> The two-step method, however, yielded very similar results.

<sup>10</sup> This is in line with other studies, which identify loan growth as a main driver of risk (see, for example, Foos, Norden and Weber (2009)).

<sup>11</sup> Note that the interest income from loans is a part of the ROA so that potential multicollinearity issues could affect the results. However, tests in which we disentangled the ROA into returns from loans and returns from remaining assets revealed that this is not a problem in our case.

out significant, and only at the 10% level. At this point, one has to keep in mind that non-traditional activities are likely to be negatively correlated with traditional activities (banks may specialize in either), which may create multicollinearity problems and hence affect the estimates. Therefore, in column four we use the ratio of commercial and industrial loans to total assets (C&I Loans/TA) instead of the loan-to-asset ratio (the traditional activity) as it is less correlated with the non-traditional activities. The result is that trading assets and for-sale securities in particular contribute 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 that non-traditional activities contribute to (tail) risk exposure. In columns five and six, we will analyze which role financial innovations play among the non-traditional 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 and positive. This is in line with our prior findings as external credit exposure is new credit exposure taken on in addition to existing exposure. Moreover, such exposure (for example, from credit enhancements) only materializes under relatively adverse scenarios, and hence should be related to tail risk. The insignificance of a bank's own securitization and asset sale activities may indicate that opposing forces are at work. On the one hand, securitization and asset sales are, by themselves, of course a mean of off-loading risk to other market participants, making a bank less risky. In particular, if the bank keeps the equity tranche but sells senior tranches it sheds tail risk relative to normal period risk. On the other hand, recent experience has shown that these activities induced banks to take on more risk<sup>12</sup>. In addition, although the credit exposure seemingly disappeared from the balance sheet to the SPV (which is legally independent), the market might expect that this separation would not survive when the SPV encounters large losses. A bank might be forced to buy back the assets from the SPV to protect its reputation and customer base (as happened in the case of Bear Stearns). Therefore, the credit exposure (which is mostly tail risk exposure) may not be effectively removed through securitization.

Column six focuses on banks' derivatives activities. Based on the available data, we can make the distinction between derivatives that are held for trading purposes and derivatives that are held for other purposes (most likely hedging). A priori one would expect that the latter would reduce tail risk. The effect for derivatives trading a priori is less clear cut. Resulting counterparty risk (which tends to materialize in tail risk scenarios) may, for example, create an increase in tail risk exposure. The results in column six show that derivatives held for trading contribute to tail risk, while the other derivatives do not seem to affect it. The latter is somewhat surprising but may be explained by the

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<sup>12</sup> For example, Franke and Krahnert (2007) and Nijskens and Wagner (2008) find that securitization increases a bank's beta.

fact that only some of these derivatives are used for hedging and that they create counterparty risk as well.

The last column takes a closer look at the importance of capital structure for tail risk. In column one we found that the leverage ratio does not contribute to tail risk exposure. We now include information on the share of deposits and the composition of deposits. In the last column of Table 1, in addition to the variables from column one, we consider the deposit-to-liabilities ratio and the ratio of time deposits above \$100,000 to domestic<sup>13</sup> deposits. Time deposits above \$100,000 are typically not insured, which makes them similar to wholesale funding, as both funding sources might be prone to runs. The results in column seven show that the leverage ratio is again not significant. Insignificance also obtains for the deposit-to-liabilities ratio. However, the time deposits above \$100,000 do contribute positively and significantly to tail risk. Since these deposits are subject to withdrawal risks similar to wholesale funding, this result is consistent with Demirgüç-Kunt and Huizinga (2009) who find that wholesale funding increases bank risk<sup>14</sup>.

## Conclusion

In this paper we propose a forward-looking method to measure (systemic) tail risk exposures at banks. Tail risk is defined as a bank's exposure to a large negative market shock and it is measured by estimating a bank's share price sensitivity to changes in far out-of-the-money put options on the market, correcting for market movements themselves. Because far out-of-the-money put options on the market only pay out if the market crashes, changes in their prices reflect changes in the perceived likelihood and severity of a crash. The estimated sensitivities, in turn, represent the market's perception of exposures to a hypothetical crash, making them a truly forward-looking measure. Another attractive feature of this measure is that it does not require the actual observation of tail risk events since it identifies banks' tail risk exposure through changes in expected market tail risk. Our measure is also relatively easy to estimate as it basically comes from an amended market regression.

The application to U.S. bank holding companies yields several interesting facts about their tail risk exposures. For example, tail risk seems to be negatively correlated with the share price beta. This suggests that banks which appear safer in normal periods are actually more crisis prone. We also find that the impact of non-traditional activities on tail risk depends on whether they leave assets on the balance sheets or not. In the former case they increase tail risk, while in the latter they do not. Our results also suggest that leverage itself does not increase tail risk, but will do so if it comes through uninsured deposits.

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<sup>13</sup> The FR Y-9C reports do not contain information on deposits in foreign subsidiaries, hence we scale by domestic deposits.

<sup>14</sup> Note that Demirgüç-Kunt and Huizinga do not distinguish between normal times risk and tail risk but focus instead on the Z-score.

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## Tables

Table 1: Relationship between Gamma and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(TA)	2.722*** (0.371)	2.934*** (0.384)	2.681*** (0.541)	2.708*** (0.492)	2.530*** (0.415)	3.237*** (0.476)	2.571*** (0.427)
Debt/TA	0.727 (29.25)	36.53 (30.54)	-21.45 (33.01)	-19.68 (30.79)	2.117 (30.08)	-6.373 (29.85)	-3.771 (29.97)
Loans/TA	23.12*** (4.433)	12.46*** (4.128)	2.485 (18.17)		23.02*** (4.44)	21.28*** (4.637)	23.16*** (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		432.5*** (37.47)					
ROA		569.3*** (57.88)					
Held-to-Maturity Securities/TA			25.62 (23.37)	23.33* (13.38)			
For-Sale Securities/TA			31.25 (21.01)	28.64*** (6.36)			
Trading Assets/TA			66.68* (34.97)	63.06*** (20.2)			
C&I Loans/TA				-0.0419 (7.882)			
Total Securitization/TA					-3.396 (6.303)		
Loans Sold/TA					-48.42 (41.47)		
Int. Cred. Exposure from Sec.& Sales					0.953 (1.486)		
Ext. Cred. Exposure from Sec.& Sales					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 <sup>2</sup>	0.23	0.239	0.23	0.23	0.23	0.23	0.23

This table reports the coefficients of the interaction terms between the adjusted put option and the respective balance sheet variables. It represents the effect of the respective balance sheet item on a bank's tail risk exposure where a positive value implies a larger exposure to tail risk. Robust standard errors are reported in parentheses and significance is denoted as follows: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



## Figures

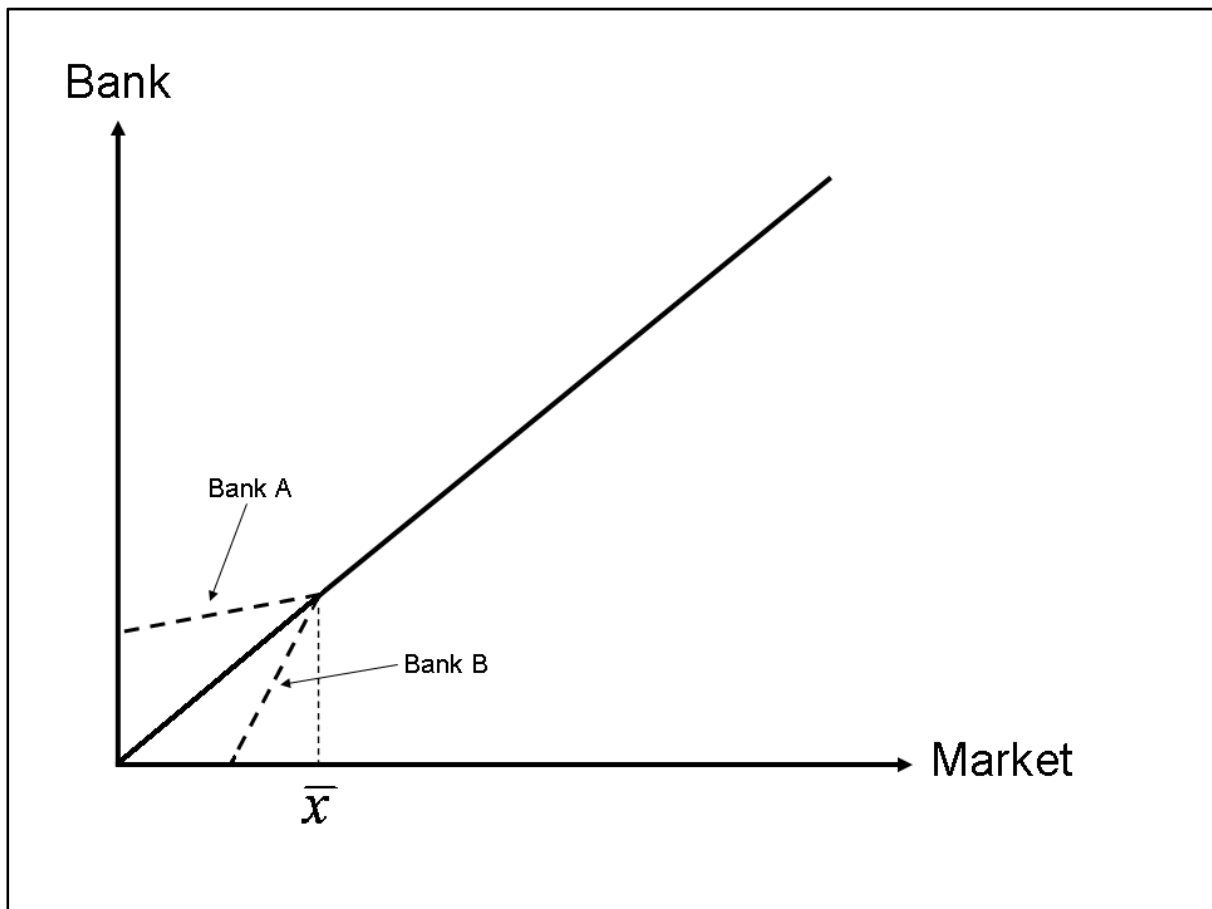


Figure 1: Relationship between Bank and Market Values

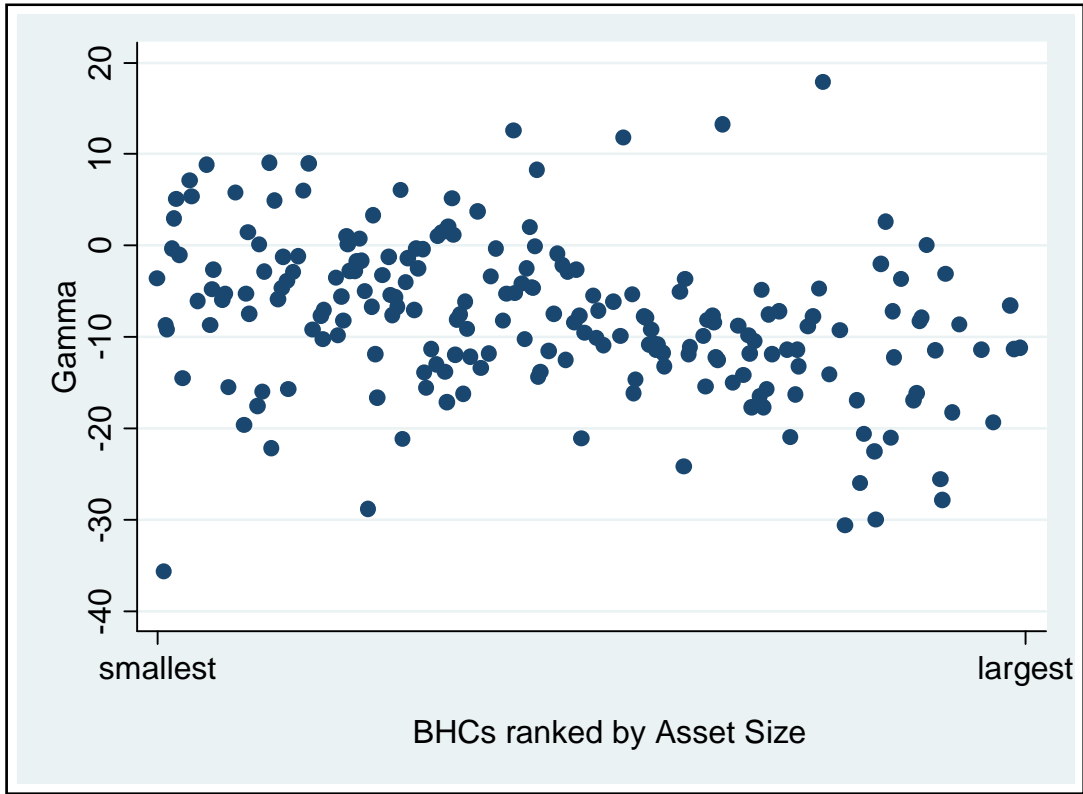


Figure 2: Tail Risk and Bank Size

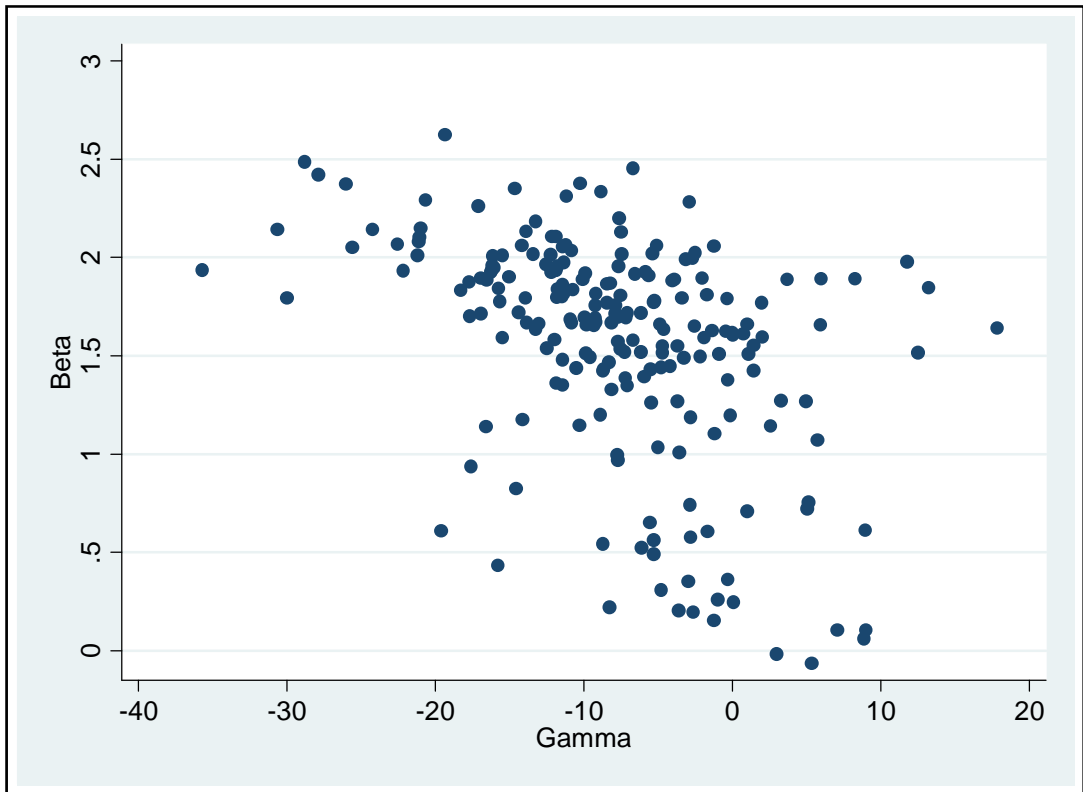


Figure 3: Gamma vs. Beta

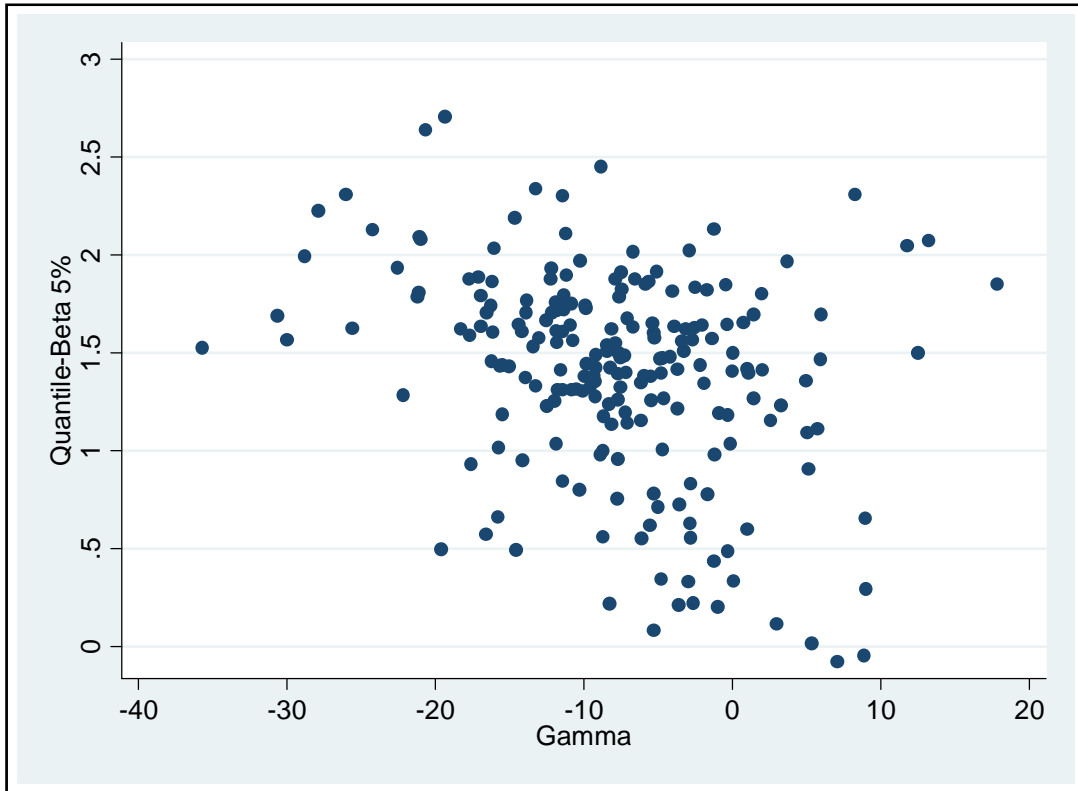


Figure 4a: Gamma vs. Quantile-Beta (5% Quantile)

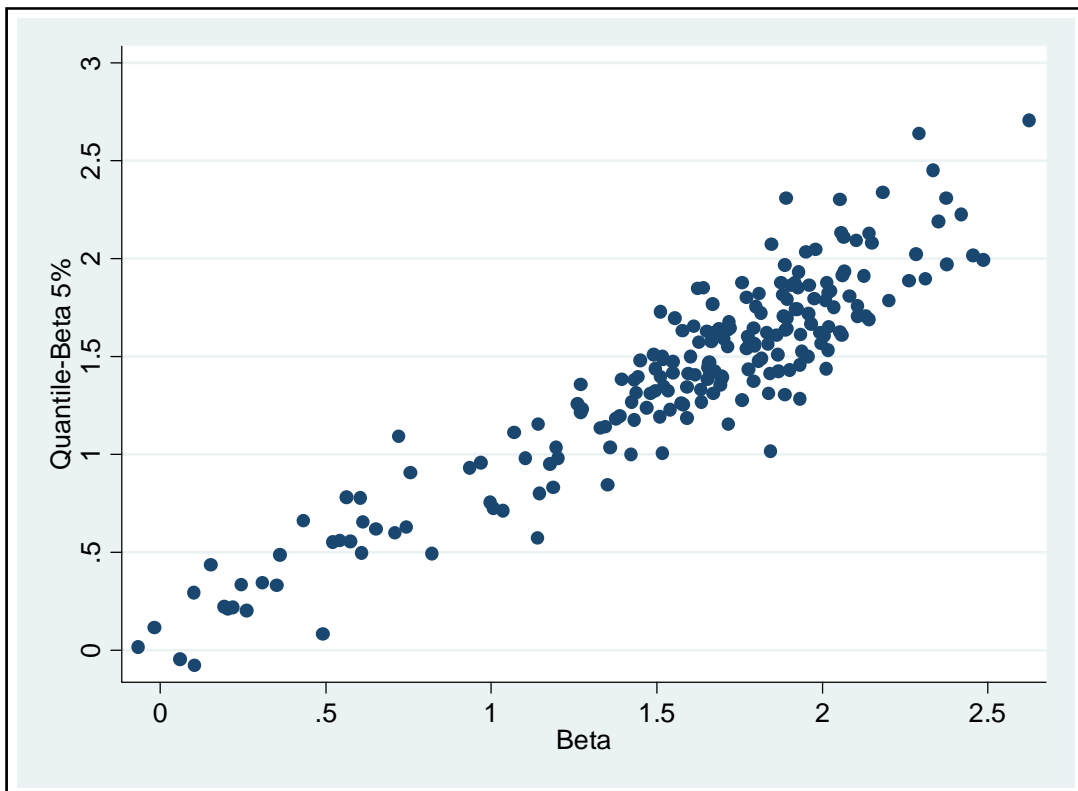


Figure 4b: Beta vs. Quantile-Beta (5% Quantile)

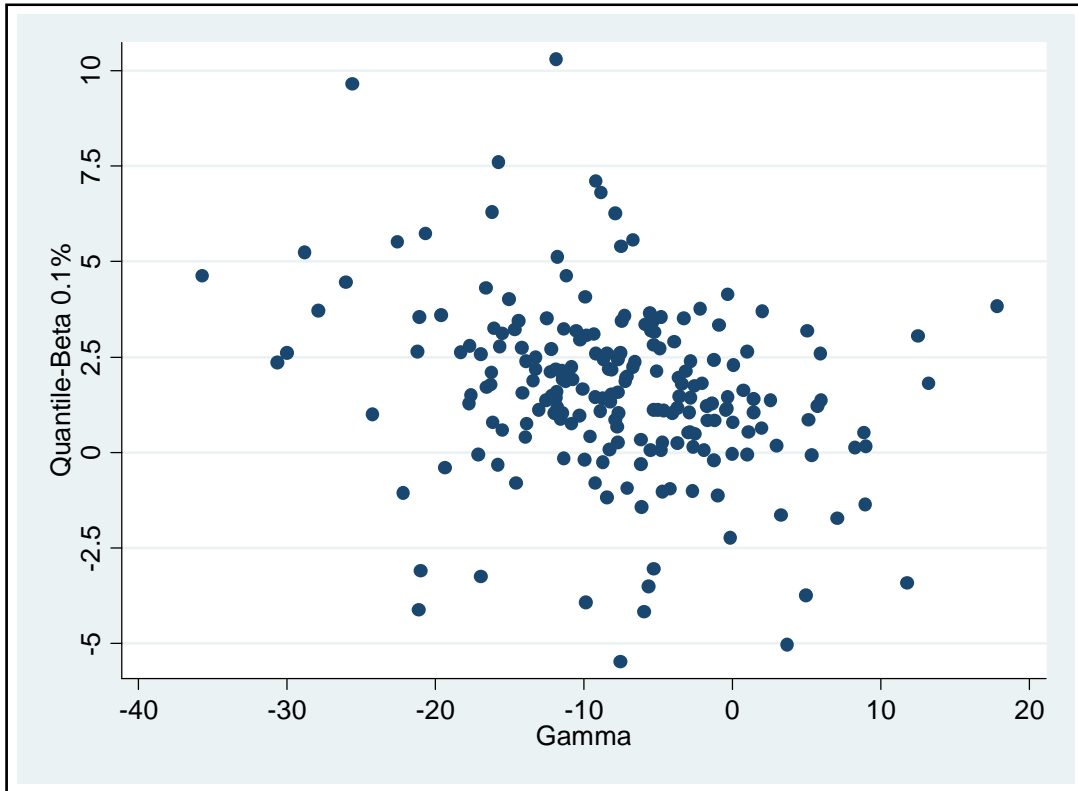


Figure 5a: Gamma vs. Quantile-Beta (0.1% Quantile)

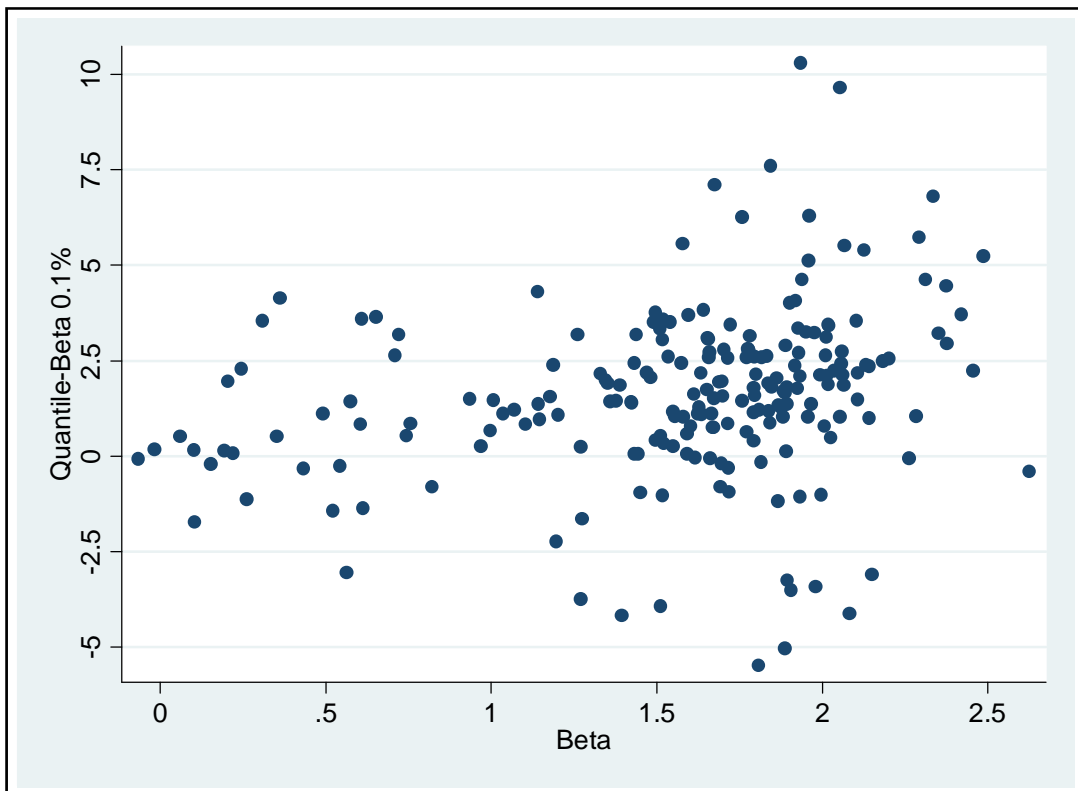


Figure 5b: Beta vs. Quantile-Beta (0.1% Quantile)