Financial Crisis: Estimating the Risk of Assets in Balance*

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Abstract

We propose a model able to estimate the risk of assets in balance from aggregate data by introducing a *prudential* measure called Filtered Historical Spectral Asset Measure (*FH-SAM*). Our measure combines a model based method to simulate the evolution of volatility with model free method of distribution. It provides a robust methodology to simulate the evolution of risk. The paper extends the debate in the literature about the tools for estimating the risk of assets for a financial institution in case of distress and systemic risk (Stiglitz et al. 2002; Lucas and McDonald 2006).

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After the burst of the housing bubble in August 2007, the financial situation in the United States and around the world has become unstable. At that time, central banks decided to take action, injecting large quantities of liquidity by purchasing securities through open market operations in order to calm the stressed interbank lending market and keep down the increasing panic. In spite of these attempts, the crisis deepened. Soon it was clear that tools and policy undertaken by the Federal Reserve Bank were not able to define and solve the catastrophic problem originated by mortgages and their securitisation.

At the end of March 2008, The Wall Street Journal announced the *imminent collapse* of Bear Stearns, followed after a few days by the agreement between the Federal Reserve and JP Morgan Chase for a $ 29 billion loan in order to support the sale of Bear Stearns.

It was the first time after the Great Depression (1929-1933) that the Fed and the US Government provided support to investment banks in an attempt to guarantee, in a consistent way, the financial system's stability.

The monetary policy intervention of the Federal Reserve reminds us of Walter Bagehot who introduced the concept of LOLR (Lender of Last Resort). According to his point of view the LOLR has to lend money as much as necessary to solvent but illiquid financial institutions for a short term, but at a penalty rate and against acceptable collateral.

Unfortunately, as the current financial turmoil shows, it is sometimes not possible to distinguish between insolvency and illiquidity and bailouts might arise moral hazard concerns.

As the financial crisis spreads into the gigantic investment banks (Citigroup, Wachovia, Lehman Brothers, Wells Fargo), not only in the United States but also around the world, governments and central banks undertook historical rescue plans in order to help a financial system in which the slogan *"too big to fail"* was replaced by *"panic and fear in the market"*.

From a financial point of view the recent crisis has shown several drawbacks of the financial system:

1. The complexity of *"creative finance"*, opacity and the scarse "risk culture" have generated

huge problems in managing risks related to financial securities.

2. The growth of volatility in financial markets has increased investors' risk aversion, leading to difficulties for banks liquidity, forcing deleverage.

3. Governance problems and perverse incentives in many financial sectors.

4. Rating agencies in conflict of interest because of their double role in consulting and evaluating issues.

5. Regulatory and bank supervision systems unable to deal with the recent turmoil.

In table I, we compare bail-out government plans in terms of interest rate cuts, capital injections (bank recapitalization and asset purchase), lending guarantees to restore liquidity; all tools aimed to rebuild investors' confidence and calm the *panic*.

[Please Insert Table I around here]

Almost all governments (US, UK, Germany, Italy, Spain, Australia, Denmark, Austria) have increased the amount of bank deposit guarantees. This choice remains controversial among economists that worry about moral hazard issues, because this policy may result in excessive risk taking on the part of depositors as well as the banks accepting the deposits.

In order to control moral hazard, central banks used a deposit insurance system consisting of "co-insurance", in which the guarantee provided to depositors was less than the total amount of individual deposits. This was meant to promote good governance practices.

Concerning liquidity and lending guarantees, Table I shows how measures adopted by central banks were totally different. For example in Denmark, Australia, Finland and Canada, the governments preferred not to provide liquidity to the system respecting the principle of *"laissez - faire"*. In China, the government reduced by about 50% the amount of reserves that each bank must hold in order to stimulate the interbank lending market. France, Germany, Spain, Japan, South Korea, US and UK preferred to inject liquidity in order to bail out troubled investment banks.

Scared about short selling and speculation, central banks of most countries (Canada, US, UK, China, South Korea, Austria, Switzerland, Sweden, Germany, France and Spain) have banned or imposed restrictions on short selling, without considering that short sellers have a crucial role for price efficiency.

Brenner and Subrahmanyam (2009) point out how *"restrictions on short selling reduce transactions in the stock market, which in turn, delays price discovery, curtails liquidity and causes prices to fall further"*. They also describe the impact of short selling on the liquidity risk of a given stock and its derivatives.

Lending guarantees and asset purchase have received plenty of attention, arising questions related to the insurance provided by governments to banks for the issue of new unsecured debt out to three years *(Guaranteed Liability)* and the potential risk of *"toxic"* assets.

In the US, all banks and financial institutions are eligible to issue senior unsecured loans with the guarantee provided by the FDIC[1]. According to the US program, each participant has to pay a "flat" fee of 75 basis points per annum on the entire sum of new unsecured liabilities. The maximum amount of liabilities that FDIC guarantees is about 125% of the outstanding senior unsecured liabilities issued by each financial institution over the next 3 years.

Acharya and Sundarum (2008) evaluate the fair value of the guarantees and the impact that a "fair price" guarantee fee may have on taxpayers, the real creditors of the troubled banks. They use three different alternatives for evaluating the insurance cost[2] and realize how the US scheme produces a *pooling* equilibrium unable to signal healthy banks and the counterparties' credit risk.

Wilson (2009), using the option pricing arguments of Merton (1974), estimates the amount of toxic assets and explains the reasons behind the illiquidity of them. According to his point of

[1]Federal Deposit Insurance Company that administers the US bail out program.

[2]median 3-years CDS + 3-years swap spread; median 3-years CDS; mid point of the previous estimates

view, the value of the put representing the guarantee [3] is very expensive to buy from shareholders and worthless to taxpayers.

Gross (2008) estimated the "fair value" of US mortgage assets via Black and Scholes formula (1973). The average value of the put option embedded in all mortgages (about \$3.6 thousand billion) is around 9.5% in the low volatility case and 12.7% in the high volatility case and the total losses on all US mortgages could amount to over \$2 trillion.

Veronesi and Zingales (2008) estimated the costs and the benefits of the Paulson Plan. They estimate the ex-ante value of the Paulson plan using Black and Scholes (1973) and Merton (1974), where the equity is an option on the value of the underlying assets and compare Paulson plan with four other alternative plans. They show how the revised Paulson plan is the most expensive for taxpayers.

Although the logic behind all these approaches is sensible, pricing within the Black and Scholes' framework (1983) is not realistic in an illiquid market, where the government is not a *"price taker"*.

We propose therefore a new prudential measure based on balance sheet data, the *Filter Historical Spectral Asset Measure* (FH-SAM) for estimating the risk of assets in balance for banks and financial institutions. Our approach combines a model based method to estimate asset variance with model-free innovations, to improve the robustness of our results. Using data provided by the Federal Reserve, we evaluate the risk of assets in balance for all US commercial banks.

The plan of our paper is as follows. In Section I, we review some important evidences related to US commercial banks. In Section II, we propose the model for evaluating the risk of assets in financial institutions. In Section III we report the estimation of the model. Our empirical results in section IV. Section V concludes.

[3] Using Black and Scholes (1973) the put option represents the value of the potential guarantee that the government has to pay in order to bailout a financial institution.

I. The US commercial banks: descriptive statistics and basic balance sheet arithmetic

I.A Commercial banks in the United States

A commercial bank is a financial intermediary owned by shareholders. It collects credit in the form of deposits, lends in the form of loans and provides other banking services to the public. It is also called a *full-service* bank.

The term commercial bank is a way to distinguish it from an investment bank that does not accept deposits or provide loans to individuals. Further, a commercial bank does not maintain broker/dealer operations and it does not offer advisory services for *corporate actions* or restructuring processes [4]. Using data from Federal Financial Institutions Examination Council, we observe a decrease of the total number of commercial banks in the United States. In Figure I, we show the evolution of the number of US commercial banks from the first quarter of 1984 (Q1:1984) to the last quarter of 2008 (Q4: 2008). The graph shows a monotonic decrease of the US commercial banks due to takeover and restructuring processes that have increased the concentration risk in the banking industry.

[Please Insert Figure I around here]

In the last quarter of 2008 (2008:Q4), the Federal Reserve estimated 6983 commercial banks in the United States, a decrease of 257 units from the second quarter of 2007.

Closer look to the data (Figure II) reveals how the number of commercial banks with average assets greater than $15 billion is slightly decreased after the burst of the credit crunch bubble, i.e. from 59 units before the crisis (Q2:2006) to 53 after the burst of the bubble (Q4:2008).

[Please Insert Figure II around here]

Further, the number of commercial banks with average amount of assets between $300 million and $1 billion is increased after the burst of the bubble, i.e. from 1101 units in the second

[4] In practice it is not sometimes possible to distinguish between a commercial bank and an investment bank, because several investment banks also act as commercial banks.

quarter of 2006 (Q2:2006) to 1192 units in the last quarter of 2008. Same trend is followed by commercial banks with an average amount of assets between $100 million and $300 million and between $1 billion and $15 billion.

Considering the recent crisis, the above bank scenario is justified. The panic and the fear in the market have generated a *bank run* in which a large number of bank customers have withdrawn their deposits from their banks. As more people withdraw their deposits, the likelihood of defaults increases, and this encourages further withdrawals.

I.B Leverage, Liquidity and Commercial Bank Balance Sheet

We consider the balance sheet of a commercial bank. The key elements are the following: bank credits (to corporate, sovereign, household and financial), interbank loans (Fed Funds and Repos with Banks), cash assets (vault cash and cashing checks for costumers), other assets[5], deposits, borrowings, other debts and owners' equity.

Figure III: ***Balance Sheet of a Commercial Bank***

Assets	***Liabilities***
Bank Credit (to corporate, sovereign and household)	**Deposits**
	Borrowings
Interbank Loans	**Other Debts**
Cash Assets	
	Owners' Equity
Other Assets	

We denominate the total amount of bank credits with $Credit_t$, the amount of interbank loans $(Int - Loans_t)$, the amount of cash assets with $Cash_t$, the value of other assets with $O - Assets_t$. From the Liability side, we name the amount of deposits with $Deposit_t$, the value of borrowings with $Borrow_t$, the amount of other debts with $O - Debts_t$ and the total amount of equity with $Equity_t$.

[5] it excludes the due-from position with related foreign offices

Using monthly data, we report time series summary statistics for all commercial banks in the United States over the period January 1973 to February 2009.

[Please Insert Table II around here]

From accounting principles, we know that the right hand side of a balance sheet has to be equal to the left hand side. So we get:

$$Credit_t + Int - Loans_t + Cash_t + O - Assets_t = Deposit_t + Borrow_t + O - Debts_t + Equity_t. \tag{1}$$

We name the left hand side of our equation as $Tot - Asset_t$ and the first three components of the right hand side equality as $Liability_t$. So we have:

$$Tot - Asset_t = Credit_t + Int - Loans_t + Cash_t + O - Assets_t \tag{2}$$

and,

$$Liability_t = Deposit_t + Borrow_t + O - Debts_t. \tag{3}$$

Starting from these basic accounting principles, we examine the health of all US commercial banks in terms of leverage and liquidity ratios and we investigate the potential relationships between these indicators.

We define leverage $(Leverage_t)$ as the ratio between the amount of total assets $(Asset_t)$ to the value of equity $(Equity_t)$. This ratio is easy to use since it requires only a cursory glance at the bank's balance sheet. Equity is simply the total amount of assets $(Asset_t)$ minus the amount of liabilities $(Liability_t)$ and includes the amount of non-redeemable preferred stock, the total value of common stock, capital surplus, permanent and statutary reserves and retained earnings. So we have:

$$Leverage_t = \frac{Asset_t}{Asset_t - Liability_t} = \frac{Asset_t}{Equity_t}. \tag{4}$$

Adrian et al. (2008) already pointed out *"the outward signs of commercial banks targeting a fixed leverage ratio"*.

Following their findings, we cast more light on the evolution of the leverage ratio. In Figure IV, we report the dynamics of total assets and the leverage ratio of all commercial banks in the United States from January 1973 to February 2009.

[Please Insert Figure IV around here]

We detect a negative trend for the time series of the leverage ratio. The leverage mean decreases from 19.75 during the period 1973-1984 with an annualized standard deviation of 15.6% to 10.56 during the period 1997-2009, with a standard deviation roughly equals to 5%. Considering the same time periods, the amount of $Equity$ has increased from a mean of 71 billion (1973-1984) to 721 billion (1997-2009) and the $Equity$ volatility has decreased from 15% to 4.7%. The total value of assets $(Asset)$ has also monotonically increased from a 1330 billion to 7419 billion and in aggregate the volatility has not changed over time (about 3%). Only *recently* we find evidence of *"commercial banks targeting a fixed leverage ratio"*.

Liquidity is another crucial factor in order to complete our analysis of all US commercial banks. Liquidity in bank management is needed for two reasons: first, to satisfy demand for new loans without having to recall existing loans or realize term investments, and second, to meet both daily and seasonal swings in deposits, so that withdrawals can be met in a timely and orderly fashion.

Liquidity inspires depositor and lender confidence. Indeed as the credit crunch crisis shows, illiquidity and poor asset quality were the main cause of bank failures. Banks were forced to close (or merge with other banks) when depositors no longer had confidence in the bank's stability (*bank run*) .

Following Grier (2002), "*liquidity is more important than asset quality because a bank with non-performing loans can continue to operate indefinitely provided that the central bank or bank regulators do not require that these assets be charged off and that the deposit levels remain stable*."

We measure the liquidity using two different ratios: the first $(First - Liquidity_t)$ relates the total amount of loans with the total amount of deposits; the second ratio $(Second - Liquidity_t)$ relates the total amount of cash assets with the amount of deposits and borrowed funds. So we have:

$$First - Liquidity_t = \frac{Loans_t}{Deposit_t}. \tag{5}$$

The term *Loans* includes commercial, industrial, real estate and consumer credits, other loans and leases. A bank that is "loaned up" has a high ratio of loans to total deposit. Liquid banks have a smaller proportion of deposits in loans and more in short-term money market investments and investment securities, both of which can readily be converted into cash that can then be loaned out.

[Please Insert Figure V around here]

The figure V shows the evolution of the first-liquidity ratio from January 1973 to February 2009. During the credit crunch crisis, the ratio decreased from 101.70% (August 2007) to 97.26% (February 2009). The ratio reflects the bank's ability to fund its loans growth with core deposits rather than borrowed funds. Due to the lack of liquidity in the banking system, the Federal Reserve has purchased *toxic* assets from commercial banks with the aim of calming down the stressed banking system. During the period, the total amount of deposits has increased by about 15% (from 6371 billion to 7331 billion) and the amount of loans has increased by about 10%.

The second indicator of liquidity $(Second - Liquidity_t)$ relates the amount of cash to the amount of deposits and borrowed funds. So we have:

$$Second - Liquidity_t = \frac{Cash_t}{Deposit_t + Borrow_t}. \tag{6}$$

After the injection of liquidity by the Federal Reserve (Septermber 2008), the second liquidity ratio increased by about 123% (from 0.039 to 0.087). Closer look to the data shows how before the credit crunch the ratio was monotonically decreasing, a strong signal that something was going wrong and that perhaps the Federal Reserve could have anticipated this catastrophic disaster[6].

[Please Insert Figure VI around here]

Now, what is the relationship between the solvency risk (leverage) and the liquidity ratios? In figure VI, we relate the first and second liquidity ratios to leverage. On the left hand side, the first liquidity ratio has been related to leverage. We can observe a negative relationship between these two indicators. It means that high is the level of illiquidity, lower will be leverage. This phenomen is justified by low capital charges on mortgage backed securities that have generated an increase in the business of these financial products and decreased the volume of loans (where the capital charges are higher) in the last few years.

On the right hand side, we capture the relationship between the second ratio of liquidity *(Second-Liquidity)* and the leverage ratio. We can oberve a positive relationship between these two indicators. It means that high it is the level of liquidity, higher it is leverage. Considering the recent financial crisis, in aggregate all US commercial banks suffered the liquidity problem and prefered to reduce leverage.

II. The Model

We start our evaluation of the amount of in balance risky assets [7] for all commercial banks in the United States from the previous evidences. According to Adrian et al. (2008), "in a financial system in which balance sheets are continuously marked to market, asset price changes appear immediately in the balance sheets of financial institutions". Although the intuition provided by the authors is sensible, problems can arise when the market-based measurement does not reflect the underlying true value. This can happen during volatile periods. Indeed during the *credit crunch* crisis, financial institutions were forced to sell assets. Liquidity was low and there was

[6] We also get the same results, if we relate the total amount of cash to the total amount of deposits. In this case, we still have a big jump of the ratio from 0.044 to 0.1163

[7] The same procedure can be used for evaluating the amount of off-balance risky assets.

fear in the market. The selling price of a bank's assets was much lower than the market value, generating a slight decrease in the shareholders' equity [8]. Being aware of this concern, we start the construction of the model using data from the balance sheet of a financial institution. Let the monthly percentage variation of total assets (r_t) be:

$$r_t = \frac{Tot\_Asset_t - Tot\_Asset_{t-1}}{Tot\_Asset_{t-1}} \backsimeq log(Tot\_Asset_t) - log(Tot\_Asset_{t-1}) = log\left(\frac{Tot\_Asset_t}{Tot\_Asset_{t-1}}\right) = R_t. \tag{7}$$

Closer look at the time series of the percentage variation of monthly total assets reveals the presence of a long term trend component (potential seasonal effects) that may lead to inconsistent estimates for the parameters of the model that we are going to build. In order to eliminate this trend, we use the Hodrick Prescott Filter (HP, 1997), aiming to isolate the short term component (c_t) from the long term component (τ_t)[9].

Under the historical measure **P**, we model the short term component c_t of asset returns, using an asymmetric Exponential GARCH(1,1) specification (Nelson 1991) with an empirical innovation density generated with the Filter Historical Simulation technique (Barone-Adesi et al. 1998).

So we have:

$$R_t = \tau_t + c_t,\ t = 1,...,T \tag{8}$$

where,

$$c_t = \varepsilon_t. \quad t = 1,...,T \tag{9}$$

The conditional mean variation is $E[c_t] = \mu$,[10] the error process ε_t is parametrized as

$$\varepsilon_t = z_t h_t^{1/2}, \quad t = 1,...,T. \tag{10}$$

[8] In April 2009, in order to avoid the forced liquidation, the Financial Accounting Standard Board (FASB) has approved new rules of evaluation based on a price that would be received in an orderly market.

[9] Consistent with the suggestions provided by Hodrick and Prescott (1997), we choose the value of the parameter that controls the smoothness (λ) equals to 14400

[10] The conditional mean variation is included in the long term component τ_t

The conditional variance process h_t follows an Exponential GARCH(1,1) model and it is described by the following equation:

$$log\,h_t = \kappa + \alpha log\,h_{t-1} + \phi\left(\mid z_{t-1} \mid - E\left[\mid z_{t-1} \mid\right]\right) + \xi z_{t-1}. \tag{11}$$

where $\{z_t\}_{t=1,..,T}$ is a sequence of detrended and scaled asset return innovations. If $\phi > 0$, a deviation of $\mid z_{t-1} \mid$from its expected value $E\left[\mid z_{t-1} \mid\right]$ implies the variance of ε_t to be larger than otherwise. The term ξ if smaller than zero accounts for the asymmetry effect, i.e negative surprises $(z_{t-1} < 0)$ raise the future asset volatility more than positive surprises $(z_{t-1} \geq 0)$of the same absolute magnitude.

In order to construct the empirical distribution of standardized detrended asset returns, we draw with replacement from our own sample of past standardized residuals, $\{\hat{z}_{t-w}\}_{w=1}^{s}$. Following Barone-Adesi et. al (1998), the random drawing is generated using a discrete uniform random variable distributed from 1 to s. This procedure permits to choose which w and so which $\hat{z}_{t-w}$ to pick from the sample of our past standardized residuals and describe the empirical distribution density of detrended asset variations. Further, we select the number of times Q in which we draw with replacement from the set of past standardized detrended asset returns and we fix the number of months K. Now, we calculate the $K-month$ percentage variation of the short term component c_t of asset returns, in the following way:

$$c_{i,t:t+K} = \sum_{k=1}^{K} \hat{c}_{i,t+k}.\;\; for\; i = 1, ..., Q \tag{12}$$

We collect the Q hypothetical $K-month$ percentage variation of detrended asset returns in a set $\{\hat{c}_{i,t:t+K}\}_{i=1}^{Q}$ and calculate the *Filtered Historical Spectral Asset Measure* (*FH-SAM*) as the weighted average of all the $\hat{c}_{i,t:t+K}s$ (where short term bad asset variations are included with bigger weights), that fall below the Value at Risk computed under the historical measure at the $100p$ percentile $\left(VaR_{t:t+K}^{p}\right)$ and on the $K-month$ distribution of the percentage variation of the short term component of asset returns.

Acerbi (2002), states that "a risk measure is coherent if it assigns bigger weights to worse cases". Following his approach, weights ω_i for computing the Filtered Historical Spectral Asset Measure $(FH - SAM)$ are as follows:

$$\omega_i = \frac{\hat{c}_{i,t:t+K} * \mathbf{1}\left(\hat{c}_{i,t:t+K} < -VaR^p_{t:t+K}\right)}{\sum_{i=1}^{Q} \hat{c}_{i,t:t+K} * \mathbf{1}\left(\hat{c}_{i,t:t+K} < -VaR^p_{t:t+K}\right)},\ for\ i = 1, ..., Q. \tag{13}$$

where, $\sum_{i=1}^{Q} \omega_i = 1$ for any finite Q.

So, we obtain:

$$FH - SAM^p_{t:t+K} = -\sum_{i=1}^{Q} \omega_i * \hat{c}_{i,t:t+K} * \mathbf{1}\left(\hat{c}_{i,t:t+K} < -VaR^p_{t:t+K}\right) \tag{14}$$

where the indicator function takes value 1 if the argument is true and zero otherwise. Further, the value at risk $VaR^p_{t:t+K}$ is computed as follows:

$$VaR^p_{t:t+K} = -Percentile\left\{\{\hat{c}_{i,t:t+K}\}_{i=1}^{Q}, 100p\right\} \tag{15}$$

with $p = 0, .., 1$.

The choice of the percentile p at a given time horizon will depend on the policy that a central bank would like to undertake in order to estimate the risky of assets in a financial institution. From one side, a value of p close to 1 will indicate a *generous forebearance policy* undertaken by the central bank; to the other side, a lower value of p will be a sign of a *strict forebearance policy.* Following Stulz (2008), we think that only an analysis based on different scenarios and horizons K might shed more light on the policy that a central bank might undertake for estimating the risk of *toxic* assets in a financial institution.

Given the choice of the percentile p and the time horizon K , we estimate the risk of assets $(FH - Risk\_Asset)$ in balance (in $ billion), in the following way:

$$FH - Risk\_Asset^p_t = FH - SAM^p_{t:t+K} * Tot\_Asset_t. \tag{16}$$

III. Estimation of the Model

In Table III, we report the estimated parameters related to the EGARCH(1,1) specification, used for computing the Filtered Historical Spectral Asset Measure (FH-SAM). The parameters κ, α, ξ, ϕ in the EGARCH(1,1) model are highly significant. Moreover, no significance is found for the constant μ in the conditional mean equation [11].

[Please Insert Table III around here]

The term $\phi\left(\mid z_{t-1}\mid - E\left[\mid z_{t-1}\mid\right]\right)$ determintes the "size effect". The parameter ϕ is equal to 0.2894 with a standard error of 0.0526. A deviation of $\mid z_{t-1}\mid$ from its expected value $E\left[\mid z_{t-1}\mid\right]$ implies the variance of ε_t to be larger than otherwise. Further, the parameter ξ, that controls for the "sign effect", is equal to -0.0799 with a standard error of 0.0360. This follows the motivation that negative surprises increase the future asset volatility more than positive surprises of the same absolute magnitude. The parameter α is equal to 0.9312 with a standard error of 0.0375, a signal of high persistency in the conditional standard deviation. The constant component κ, in the conditional variance process is equal to -0.6665 with a standard error of 0.3161.

[Please Insert Figure VII around here]

In figure VII, we plot the dynamics of the conditional standard deviations, the ordinary and standardized residuals. The Exponential GARCH specification is well enough able to capture the evolution of the volatility related to the detrended time series of monthly assets. Indeed, we can observe how the volatility is increased after the burst of the Housing Bubble (August 2007), achieving the level of 0.021(November 2008).

To measure the goodness of fit of our model, in Table IV we report several in-sample and out-of-sample statistics: the log-likelihood statistics (Log-likelihood), the R-squared (R^2), the root mean square error (RMSE) and the mean absolute error (MAE).

[11] We also estimate the parameters for the EGARCH(1,1) specification used for computing the Filtered Historical Spectral Equity Measure (FH-SEM). Also in this case, we found the parameters of the variance process highly significant and the constant in the mean equation no significant.

[Please Insert Table IV around here]

The Log-likelihood statistics is equal to 1544 and the R^2 (goodness of fit for the model) is equal to 0.00373. The last two performance measures evaluate the forecasting power of the model using August 2007 to February 2009 as out-of-sample period. The average absolute error that we compute (MAE) is equal to 0.0120 and the root mean square error equals to 0.0158[12].

IV. Empirical Results: Risk Measures for all US Commercial Banks

We apply our model, using the time series of monthly total assets for all US commercial banks from January 1973 to February 2009 [13]. The data are unseasonalized, consolidated and released publicly on the Board of Governors of the Federal Reserve System website [14].

We show 90%, 95% and 99% FH-SAM estimates for several horizons 6, 12, 18, 24, 30, 36 months from February 2009, simulating 50000 paths . Further, we compare our methodology with 90%, 95% and 99% Value at Risk and Expected Shortfall [15].

We assign bigger weights to worse cases, improving the reliability of the tail index estimator and providing more conservative estimates of the risk of assets in balance (panel A). Different levels of FH-SAM measures estimated at different time horizons might be optimal for assessing the risk of assets in a financial institution. For example, FH-SAM measures at 99% with horizons of 6 and 36 months (from February 2009) estimate a risk in the amount of total assets for 9.03% and 16.61%. Using the previous critical value, the potential loss will be respectively equal to $1087.24 billion for a time horizon of 6 months and $2000.06 billion considering a horizon of 36 months (panel B). Considering FH-SAM measures at 90% with horizons of 6 and 36 months from February 2009, we respectively estimate the risk of assets in balance for $ 711.27 billion and $1314.93 billion.

[12] We also computed the forecasting power of the model using January 2002 to February 2009 as out-of-sample period. The results that we get are even better. The average absolute error is equal to 0.0093 and the root mean square error is 0.0064.

[13] Unfortunately, the Federal Reserve does not provide time series data that takes into account corporate action (M&As, spin-offs etc) effects and it seems unrealistic try to exploit a procedure able to get rid of these effects due to the large number of corporate actions related to all US Commercial Banks.

[14] www.federalreserve.gov/releases/h8/data.htm

[15] The last two risk measures are computed using an EGARCH(1,1) for capturing the dynamics of the volatility and the filtered historical simulation for constructing the empirical distribution.

We cast more light on the balance sheet of all US commercial banks and we construct the Filtered Historical Spectral Equity Measure (FH-SEM), with the same methodology used for computing the FH-SAM measure [16].

[Please Insert Table V around here]

Table V reports the estimates related to the FH-SEM measures. With a critical value of 99%, the risk of equity that we estimate in 6 months (from February 2009) is equal to 13.35% of the entire amount of equity. This percentage increases to 50.21%, if we consider a time horizon of 36 months.

Conclusions

The paper extends the debate in the literature about the tools for evaluating the risky of assets in balance for a financial institution in case of distress and systemic risk (Stiglitz et al. 2002; Lucas and McDonald 2006). We propose the Filtered Historical Spectral Asset Measure (FH-SAM) that generates scenarios for the evolution of risk through the combination of dynamic variance model and non parametric innovations. Using monthly aggregate balance sheet data for all US commercial banks from January 1973 to February 2009, we use our approach for estimating the risk of assets in balance. Following Stulz (2008), we think that only an analysis based on different horizons and scenarios might shed more light on the prudential policy that a central bank might undertake. The choice of the percentile p used for estimating our measure will be close to 1, if the Federal Reserve would like to undertake a *generous forebearance policy*; to the other side, a lower value of p will be a sign of a *strict forebearance policy.*

[16]Indeed, we model the percentage detrended monthly variation of shareholder's equity using an EGARCH(1,1) specification. As the previous methodology, we use the filtered historical simulation (Barone-Adesi et al. (1998)) for constructing the empirical distribution of hypothetical future detrended equity variations and we calculate the FH-SEM at different critical values (90%, 95%, 99%) and different time horizons (6, 12, 18, 24, 30, 36 months) from February 2009.

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(Source: Financial Times 10/17/2008)

Table I: ***Government intervention plans***

The Table (panels A, B, C, D, E) reports the government intervention plans in terms of liquidity and lending guarantees, interest rate moves, bank deposit guarantees, bank recapitalization, asset purchase and short selling crackdown

Panel A:

The panel reports Canada, United States (US) and United Kingdom (UK) intervention plans

	Canada	**US**	**UK**
Liquidity and Lending Guarantees		Government guarantees all senior debt issued by banks over next 3 years	Government guarantees new short and medium term debt by the banks, backing as much as £250bn of borrowing +£100bn (swap illiquid assets to Tbills)
Interest Rate Moves	Cut rates: 2.5% on Oct 8 2008	Cut rates: 1.5% on Oct 8 2008	Cut rates: 4.5% on Oct 8 2008
Bank Deposit Guarantees		Increased guarantee to $ 250000 per depositor; unlimited guarantees on deposits that do not bear interest	Increased guarantee to £ 50000 per depositor from £ 35000
Bank Recapitalization		Rescue package for $700bn; up to 250bn to buy preferred stocks in 9 “big” banks	£25bn available to increase the Tier1 ratio RBS, HBOS and Lloyds take £39 bn injections and so partly nationalized.
Asset Purchase		Up to $100bn used to buy troubled bank assets	
Short Selling Crackdown	Temporarily banned short selling on 13 financial instit. ban lifted on Oct 8 2008	Temporarily banned short selling on 900 financial institutions; ban lifted on Oct 8 2008	Temporarily banned short selling on 34 financial institutions stocks till Jan 16 2009

Panel B:

The panel reports France, Germany, Italy and Spain intervention plans

	France	**Germany**	**Italy**	**Spain**
Liquidity and Lending Guarantees	Government provides €320bn to guarantee banks	Government provides €400bn to guarantee banks	Up to € 40bn in treasury bills for refinancing against inferior assets	Government guarantees up to € 100bn for 2008 + further amount in 2009
Interest Rate moves				
Bank deposit Guarantees		Guarantees provided for all private German bank accounts	Deposits up to € 103000 guaranteed	Guarantees to € 100000
Bank Recapitalization	Government set up a plan of €40bn to take stakes in companies	+ € 100bn to recapitalize banks	Emergency plans to buy non voting assets in troubled banks	Measures approved: Government may buy bank shares
Asset Purchase				
Short Selling Crackdown	Temporarily banned short selling on banks and insurance comp. from Sept 22 2008 for 3 months	Banned short selling on 11 financial stocks till the end of the year	Shorters must have stocks available from moment placed	Banned naked short sell + any position > 0.25% mkt cap must be disclosed

Panel C:

The panel reports Switzerland, Norway, Finland and Sweden intervention plans

	Switzerland	**Norway**	**Finland**	**Sweden**
Liquidity and Lending Guarantees		Government bonds in exchange for mortgage debt (amount of $ 55.4bn)		Government guarantees more liquidity in the mkt with a plan of $ 205bn
Interest Rate moves	Cut rates: 4.25% on Oct 8			Cut Rates: 3.75% on Oct 23
Bank deposit Guarantees			Deposits up to € 50000 from $25000	Guarantees to $ 69000 + guaranteed deposits at foreign banks with Sweden clients
Bank Recapitalization	Government took an indirect Sfr 6bn stake in UBS			Government set up a plan of SKr 15bn to take stakes in any bank
Asset Purchase	A new entity controlled by SNB to take over $ 60bn of UBS' illiquid US securities			
Short Selling Crackdown	Banned naked short selling			Banned naked short sell + any position > 0.25% mkt cap must be disclosed

Panel D:

The panel reports Denmark, Netherlands, Belgium and Austria intervention plans

	Denmark	Netherlands	Belgium	Austria
Liquidity and Lending Guarantees		Government guarantees € 200bn in interbank lending	Guaranteed all new financing by banks for one year	Government provides € 85bn to guarantee bank lending
Interest Rate moves				
Bank deposit Guarantees	All bank deposits guaranteed from a $ 6.5bn liquidation fund			Unlimited guarantees
Bank Recapitalization		Government to spend $ 20bn to recapitalize banks ING got € 10bn	Injection of € 4.7bn to Fortis against a 49% stake	Government injects € 15bn to boost bank capital
Asset Purchase				
Short Selling Crackdown		Banned Short Selling in 8 financial institutions for 3 months		Short selling over a certain threshold can be considered as market manipulation or insider trading

Panel E:

The panel reports China, Japan, South Korea and Australia intervention plans

	China	**Japan**	**South Korea**	**Australia**
Liquidity and Lending Guarantees	Reduced for 50% the amount that each bank must hold in reserve	Injection of $ 20bn on Oct 8 2008	Government injects + $ 45bn into banks + buying repurchasing agreements and gov. bonds	
Interest Rate moves	Cut Rates: 6.93% on Oct 8 2008		Cut Rates: 5% on Oct 9 2008	
Bank deposit Guarantees			Provided guarantees if Korean banks take up external debt	Since A$ 700bn guaranteed for 3 years
Bank Recapitalization		Government buys companies' shares and suspends the sale of government-owned stocks	Won 12000bn in fresh loans to small and mid - sized companies	Government injects € 15bn to boost bank capital
Asset Purchase				Approved plan to purchase A$ 8bn of residential mortgage backed securities
Short Selling Crackdown	Banned Short Selling	Existence of adequate rules	Banned Short Selling	Banned Short Selling

(Source: Federal Financial Institutions Examination Council)

Figure II : ***Total Number of US commercial banks***

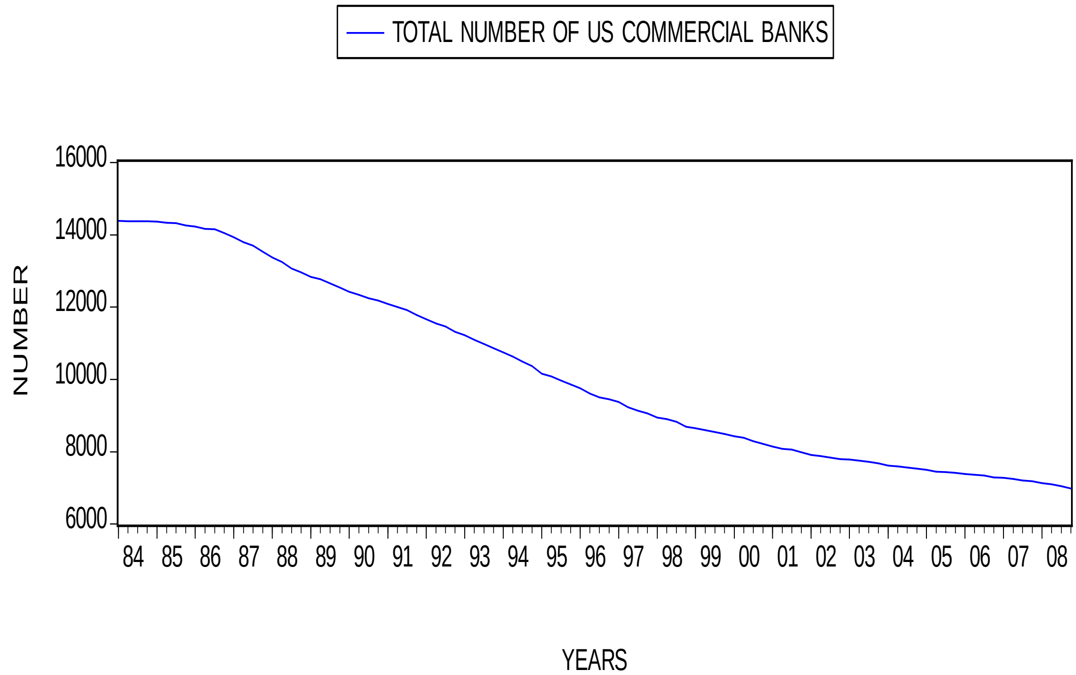

Figure III: ***US commercial banks classified by amount of average assets***

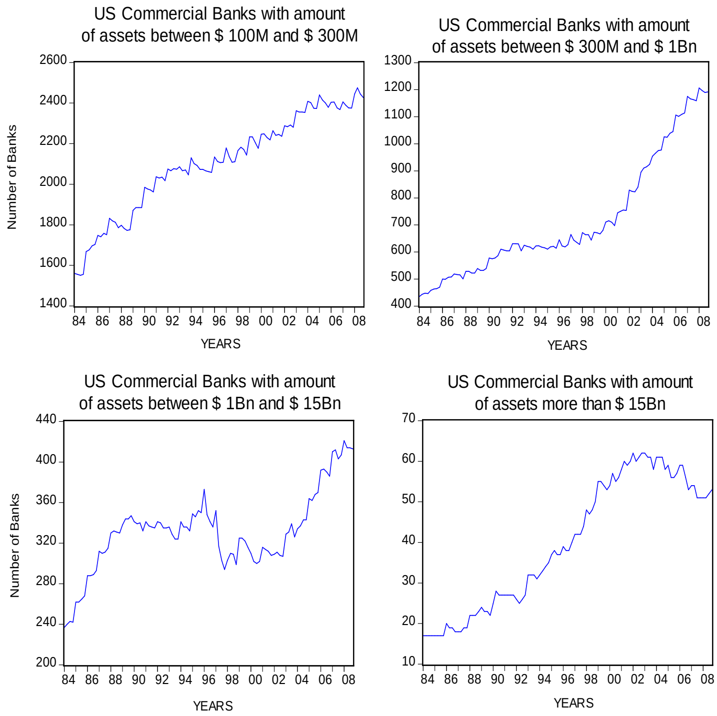

Table II : ***Commercial Banks Summary Statistics***

The table reports time series summary statistics for all commercial banks in the United States using monthly data from January 1973 to February 2009.

	Mean	Std Dev	Min	Median	Max	Observations
CREDIT	3372.98	2458.10	568.20	2765.85	9997.10	434
CASH	226.99	98.15	80.30	225.80	1041.60	434
INT-LOANS	179.75	103.96	27.50	166.10	464.30	434
O-ASSETS	244.58	235.09	20.80	144.45	1007.90	434
ASSETS	4024.30	2862.84	701.60	3322.10	12422.90	434
DEPOSIT	2661.61	1703.48	596.30	2369.00	7365.00	434
BORROW	723.44	628.28	45.70	507.75	2654.20	434
O-DEBTS	287.22	236.89	25.70	161.65	1393.50	434
EQUITY	352.04	314.97	33.90	250.85	1213.30	434
LIABILITY	3672.26	2549.31	667.70	3069.75	11232.80	434

Figure IV: ***Leverage and Total Assets***

On the left hand side, we plot the dynamics of the leverage ratio and the amount of total assets for all US Commercial Banks from January 1973 to February 2009. On the right hand side, we relate the leverage ratio against the amount of total assets.

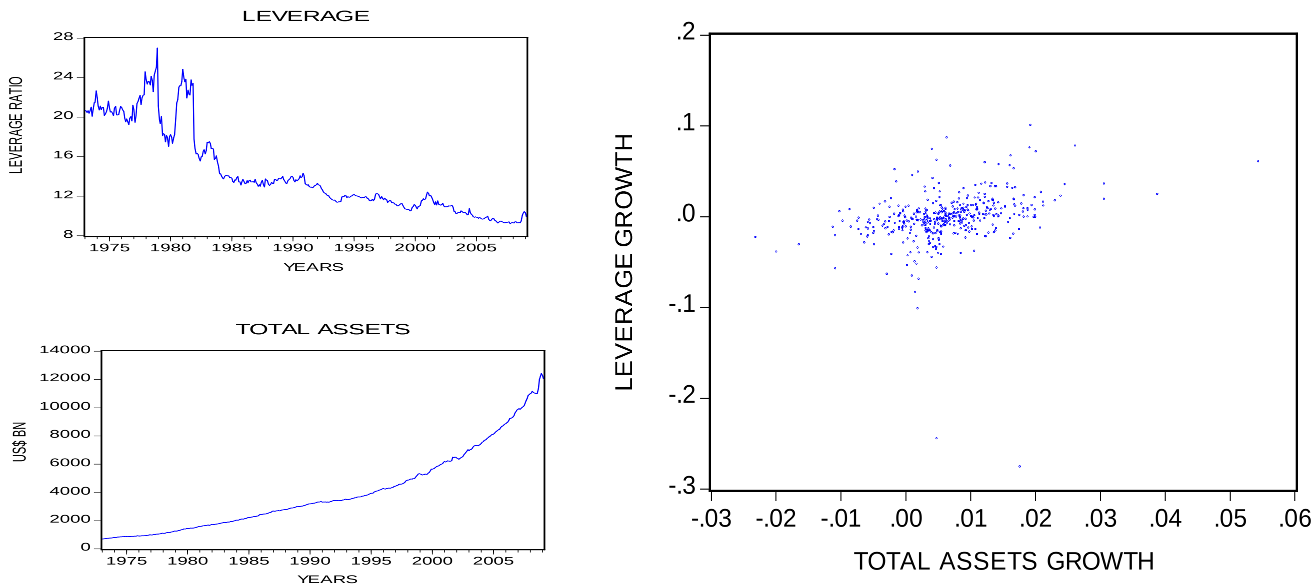

Figure V: ***Liquidity Ratios***

The figure shows the dynamics of the first and second liquidity ratios for all commercial banks in the United States, from January 1973 to February 2009. The first liquidity ratio is computed relating the amount of loans to the total amount of deposits; the second is computed relating the amount of cash to the total amount of deposits and borrowed funds.

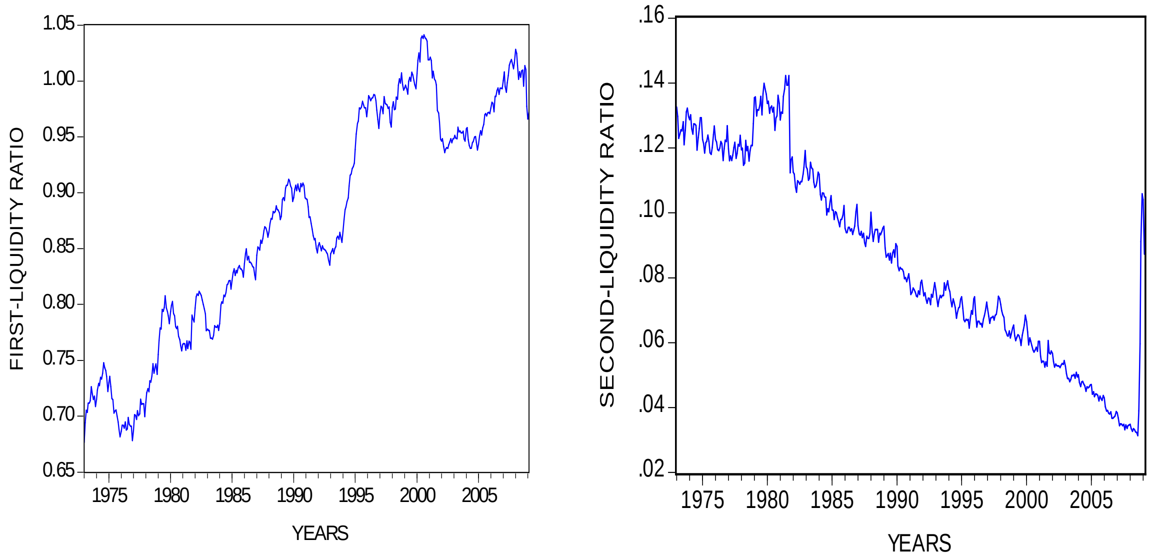

Figure VI: ***Leverage and Liquidity Ratios***

The figure shows the relationship between leverage and liquidity ratios for all commercial banks in the United States, from January 1973 to February 2009. The first liquidity ratio is computed relating the amount of loans to the total amount of deposits; the second liquidity ratio is computed relating the amount of cash to the total amount of deposits and borrowed funds; the leverage is equal to the amount of total assets to the amount of equity.

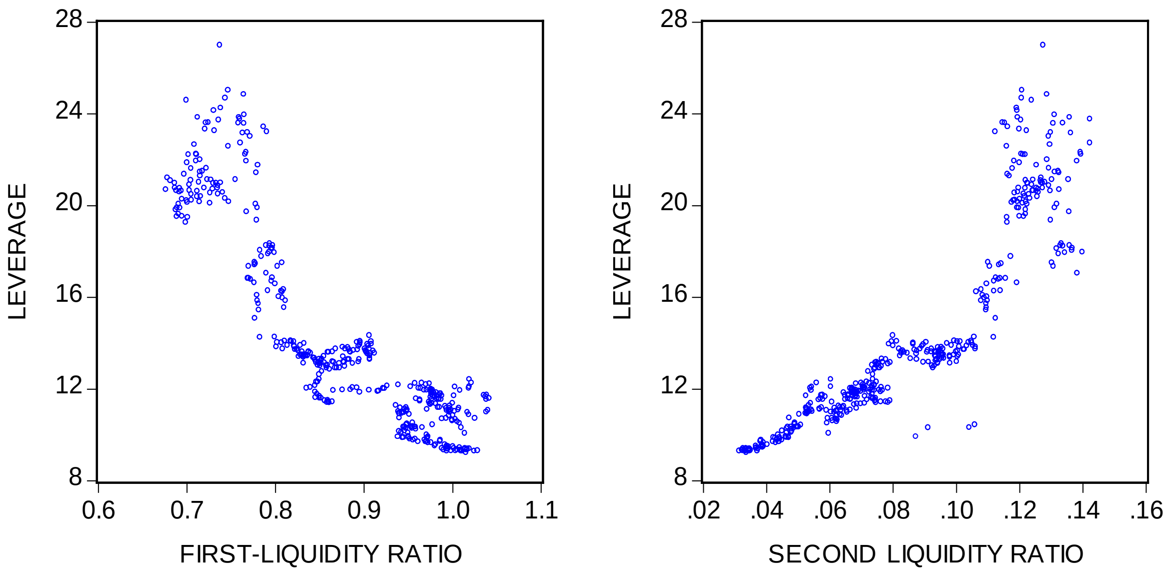

Table III

The Table reports estimated parameters of the EGARCH(1,1) model used for capturing the conditional variance h_t related to the amount of monthly total assets. Asterisks denote significance at the 5% level or better.We use the period January 1973 to February 2009 for estimating the parameters used for computing the Filtered Historical Spectral Asset Measure (FH-SAM).

Panel A: Estimated parameters of the EGARCH(1,1) model

Parameter	Value	Standard Error	T Statistic
μ	0.0005	0.0003	1.4108
k	-0.6665^*	0.3161	-2.1024
α	0.9312^*	0.0375	24.8355
ϕ	0.2894^*	0.0526	5.5011
ξ	-0.0799^*	0.0360	-2.2222

Table IV

The Table reports several in-sample and out-of-sample statistics. The log-likelihood statistics (Log-likelihood), the R-squared (R^2), the root mean square error (RMSE), the mean absolute error (MAE).In particular the last two measures capture the forecasting power of the EGARCH(1,1) specification for the period August 2007 to February 2009.

	Log-likelihood	R^2	RMSE	MAE
Performance	1544.00	0.00373	0.0158	0.0120

Figure VII: *Volatility, Residuals and Standardized Residuals*

The figure plots the conditional standard deviations, the ordinary and standardized residuals related to the amount of detredend monthly assets.

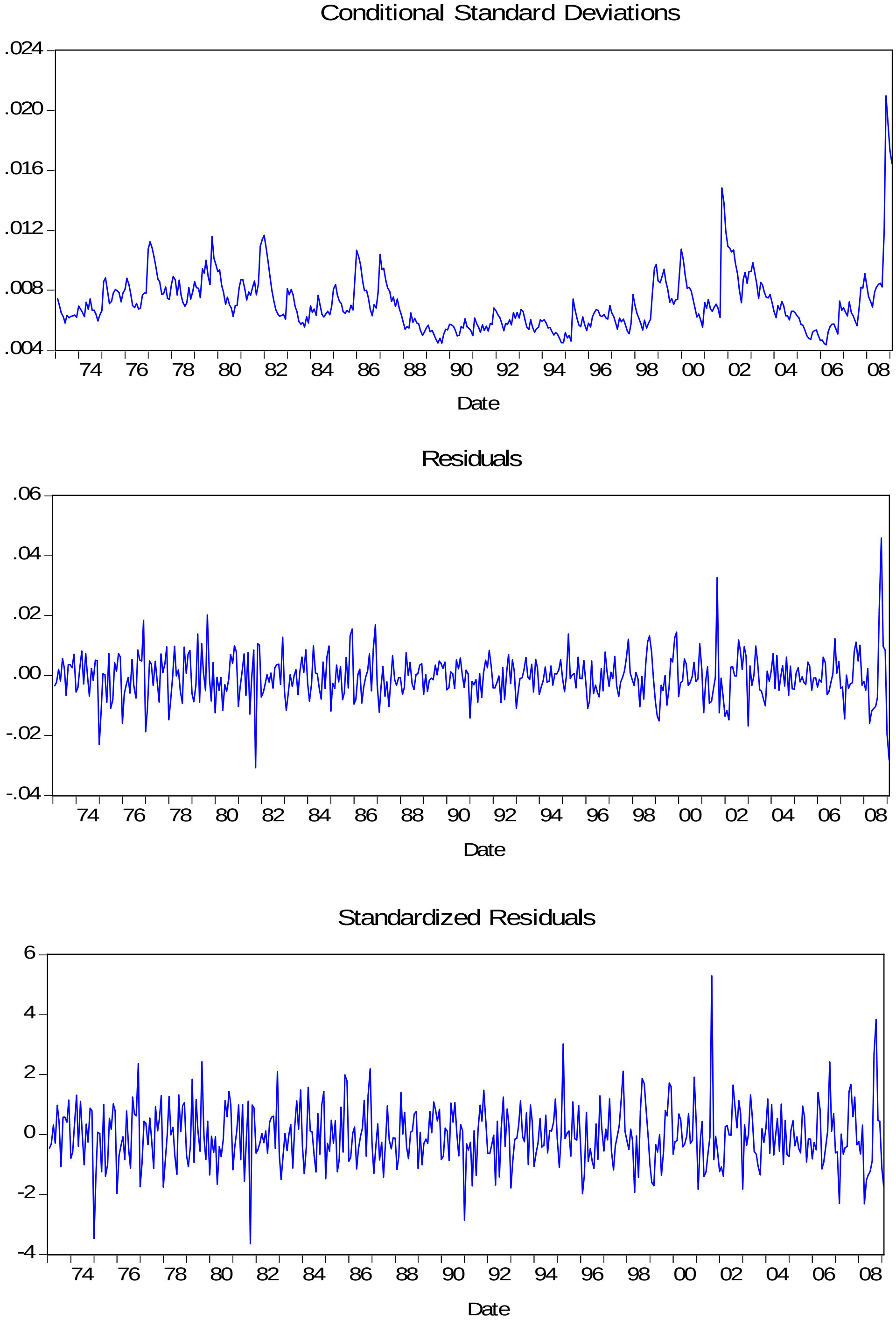

Table IV: *Risk Measures for all US Commercial Banks*

This table reports the values of the Filtered Historical Spectral Asset Measure (FH-SAM) estimated at 90%, 95% and 99%, using horizons of 6, 12, 18, 24, 30, 36 months from February 2009 for all US Commercial Banks. In Panel A, we report and compare the levels of our methodology with the Value at Risk and the Expected Shortfall for several horizons and different critical values. In panel B, we estimate the risk of assets in balance (in billion of dollars) related to all US commercial banks at 6, 12, 18, 24, 30, 36 months from February 2009.

Panel A: *Risk Measures related to Assets for all US Commercial Banks*

HORIZON	90%			95%			99%		
	VaR	Exp. Short.	FH-SAM	VaR	Exp. Short.	FH-SAM	VaR	Exp. Short.	FH-SAM
6 MONTHS	4.31%	5.55%	5.91%	5.57%	6.58%	6.87%	8.29%	8.80%	9.03%
12 MONTHS	5.46%	7.64%	8.20%	7.04%	9.11%	9.56%	10.4%	12.33%	12.66%
18 MONTHS	6.19%	8.13%	8.66%	7.98%	9.70%	10.12%	11.65%	13.04%	13.40%
24 MONTHS	6.57%	9.23%	9.90%	8.52%	11.03%	11.53%	12.47%	14.82%	15.14%
30 MONTHS	6.99%	9.75%	10.40%	9.06%	11.56%	12.06%	13.17%	15.42%	15.76%
36 MONTHS	7.27%	10.20%	10.92%	9.42%	12.18%	12.71%	13.88%	16.27%	16.61%

Panel B: *Using the FH-SAM at different time horizons (6, 12, 18, 24, 20, 36 months) and percentage levels (90%, 95%, 99%). We report the risk of assets (in billion of dollars) in balance for all US commercial banks from February 2009 .*

HORIZON	FH-SAM 90%	FH-SAM 95%	FH-SAM 99%
6 MONTHS	711.27	827.35	1087.24
12 MONTHS	987.75	1151.01	1524.98
18 MONTHS	1042.58	1219.22	1613.79
24 MONTHS	1191.75	1388.25	1823.78
30 MONTHS	1252.25	1452.46	1897.55
36 MONTHS	1314.93	1530.39	2000.06

Table V: ***Filtered Historical Spectral Equity Measure (FH-SEM) for all US Commercial Banks***

This table reports the values of the Filtered Historical Spectral Equity Measure (FH-SEM) estimated at 90%, 95% and 99%, using horizons of 6, 12, 18, 24, 30, 36 months from Fenruary 2009 for all US Commercial Banks.

HORIZON	FH-SEM 90%	FH-SEM 95%	FH-SEM 99%
6 MONTHS	7.55%	9.14%	13.35%
12 MONTHS	8.54%	10.25%	14.63%
18 MONTHS	16.21%	19.84%	29.99%
24 MONTHS	20.14%	24.74%	37.89%
30 MONTHS	23.52%	28.95%	44.74%
36 MONTHS	26.73%	32.83%	50.21%