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FULL DISCLOSURE AND FINANCIAL STABILITY: HOW DOES THE MARKET DIGEST THE TRANSPARENCY SHOCK?[1]

Fausto Pacicco[*], *Luigi Vena*[**], *Andrea Venegoni*[***]

1. Introduction

The 2008 financial crisis can be described as a large-scale modern bank run. As the literature tells us, the trigger of such runs is the publics uncertainty about the solvency ability of banks, *id est* a lack of overall transparency which causes panic in agents who withdraw their money from financial institutions vaults (Diamond and Dybvig, 1983). The modern version of this narrative sees banks investors and even insiders, unable to assess the quality of banks portfolios, the extension of their exposure to the so-called “toxic” assets and their solvency. This brought banks stocks to trade at rates that were overly discounted and even the interbank market froze as banks were not able to evaluate their peers conditions any longer. As Flannery et al. (2013) argue, behind this mechanism there was a dramatic increase in the information asymmetry of the financial system. Public authorities promptly sought to tackle this problem but soon realized that they did not have at their disposal an efficient crisis management tool which could allow them to curb the panic and restore confidence.

In such a distressed environment, regulators had to concentrate their efforts in reassuring the market about the solvency ability of the single banks, and on their resilience to possible further turmoil. The first to act was the Federal Reserve Bank that, in early 2009, designed and ran an unprecedented supervisory exercise, the Supervisory Capital Assessment Program (SCAP henceforth), with the declared aim to ensure adequate capital to promote lending and restore investor confidence (Hirtle et al., 2009). The valuable information contribution of the SCAP has been recently tested empirically, among others, by Morgan et al. (2014) and Neretina et al. (2014) proving that this exercise can convey significant new data to the market which in turn

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improves its ability to evaluate banks assets and solvency. Many commentators have attributed this success to the choice of fully disclose the results by communicating to the market all the bank specific findings. This decision has been highly debated in the academic world as there are doubts about the public's reaction to the disclosure of such critical information. Goldstein and Sapra (2013) claim that, in a crisis situation, disclosure has indeed beneficial effects but, since financial markets are featured by strategic environments, agents may give excessive weight to public reactions, disregarding fundamentals. If so happens, market price information content is bound to decrease and hence market discipline is harmed. Following this line, the main concern on a full disclosure stems from the fear that, contrary to conventional wisdom, it can add further pressure to already distressed institutions (Spargoli, 2013; Cordella and Yeyati, 1998). Banks, forced to adequate capital to the risk exposure, can be compelled to downsize as bad news about their capital provision may cause the exclusion from the funding market. If such an outcome occurs, stress tests would completely fall short of expectations as the policy purpose behind their implementation is to revive the funding market and ease banks access to fresh capital injections. Hence, stress tests may have a considerable announcement effect changing the expectations of agents on the supervisory stance (as proved for the European Comprehensive Assessment by Lazzari et al. (2016)). In light of this, it has become crucial to assess how markets risk perception would change in the event of such a disclosure, in order to make authorities able to implement a results communication policy that best addresses the task of stabilizing the banking system by restoring confidence in it when needed.

The key question then is: how does the market digest a transparency shock? Moreover, how does public risk perception change according to the single banks performance in this kind of exercises? Our paper aims at empirically assessing how the public updates its risk assessment of banks, following the disclosure of stress tests results. In particular, we want to understand what the market infers on the riskiness of each single institution, primarily about the ones who end up to be undercapitalized. The estimation of market reactions is not a trivial exercise: indeed, it requires a model that is able to estimate time varying parameters and to adopt an algorithm that recursively learns from the improved information set. Doing so, we are able to infer if, when and how the market updated its risk perception in the presence of new information without the need of a priori assumptions. Among the many statistical specifications which are able to tackle such issues (Das and Ghoshal, 2010), we have decided to apply a non-Gaussian state space representation of a Fama-French three factors model estimated (henceforth 3FM) with a Kalman Filter as we believe it can face the trade-off between simplicity and misspecifications avoidance. The market beta will be our proxy for the public risk perception of each banks securities.

We analyze how the market uses the information disclosed through the SCAP as it is the only exercise which has been ran up to now (both in Europe and in U.S.) that literature unanimously identifies as an effective new information provider. Our work gives a contribution to the existing literature both on the methodological and on the theoretical sides providing a framework which is able to evaluate the effect of a transparency shock on the risk perception of the public.

Empirically, we develop a framework that dynamically evaluates the evolution of markets risk perception by observing the presence of patterns of betas over time and appreciating any reactions to given events. On the theoretical side, our contribution is twofold: on one hand, it adds to literature on the information contribution of the stress test, by focusing on how the market interprets it rather than investigating whether it has received the information. Secondly, we provide an empirical contribution to the debate on the effects of authorities' communications of supervisory findings and enhanced transparency.

Contrarily to the claim that banks with negative outcomes may suffer additional pressure and might experience difficulties in raising capital or even a run, we find that, for the SCAP case, the market revised its risk assessment downwards for nearly all banks, no matter if they passed or failed the exercise. This suggests to rule out the separating equilibrium effect hypothesis as the market revised its risk perception in the same direction regardless to the single institutions performance. The betas of almost all banks and of the portfolio which groups them all, decrease in the first months of 2009, when the test ran and the results were disclosed, and stay at steady low levels for nearly a year suggesting that the transparency shock has not only a short term effect but also a soothing influence on the markets in the medium run. Our findings support the claim that full disclosure in crisis times can play a key role in reviving the financial and economic system, as long as the policy intervention is well designed and regulators are able to pose a credible recapitalization threat to institutions (see Spargoli, 2013). One possible interpretation is that such a supervisory effort, along with the commitment to fully disclose the results to the market, is read by the agents as a signal of a more severe future policy stance and, hence, contributes in enhancing confidence in its perspective stability; the recapitalization threat represents a fundamental feature, as a mean to assure the market that even undercapitalized banks will be provided with enough capital to securely remain in business.

2. Literature Background

There is a widespread belief that the 2008 financial crisis is strongly related to the lack of transparency of the banking system (e.g. Morgan et al., 2014; Schuermann, 2014; Flannery et al., 2013). The inability showed by banks investors to assess the composition of financial institutions portfolios and the riskiness of some assets, that could have been included in them, was a clear sign of the severe information asymmetry affecting the system. This lead to a diffused inability in the evaluation of the solvency and perspective soundness of each bank, bringing investors to hugely underprice banks stocks. The situation eventually degenerated in what seemed to be an unprecedented large scale bank run (Morgan et al., 2014). In order to fix these information asymmetry problems, that were the main driver of such a dynamic, and to restore an acceptable degree of transparency, the authorities designed and implemented the SCAP, commonly known as the banks stress test. This program involved the 19 largest U.S. bank holding companies (BHC henceforth), representing almost the 67% of the total bank assets. Each bank had to make a two years ahead projection of the perspective performance under two economic scenarios. Those projections were then checked and revised by the supervisors, yielding a final projection of banks performance that concurred in the determination of the so-called pro-forma capital. The difference between this measure and the capital threshold set by the regulator was going to determine the capital need of the single institution. Banks that found themselves with a capital gap were required to file a plan which had to explain the measures intended to fill this gap by November 2009. Between the participating institutions ten were deemed to need a capital injection, while the remaining nine proved to be adequately capitalized.

The SCAP marked a turning point in the supervisory practice setting standards for following implementations: comparability of results, absolute transparency and assurance about future resilience of each bank. Especially for what concerns the transparency issue, this exercise indicated a clear breakpoint with the usual supervisory practices: every feature was fully disclosed to the market, from the beginning, when assumptions and procedures were modelled, to the end, when the whole mechanism functioning and the results were published.

Immediately after the publication of the results, the debate started to inflame on the efficacy of such a procedure and on the opportunity to replicate it in others contexts. Both academic and policy makers seem to agree that the SCAP experience was decisive in restoring an acceptable degree of confidence in the soundness and future perspectives of the financial system springing the spark of the economic recovery. Morgan et al. (2014) find that there were significant abnormal returns both in the so-called clarification date (February 23-25, 2009), when the authorities made clear what should have been the treatment for banks with insufficient capital, and in the following *disclosure date* (May 7, 2009) of results. Neretina et al. (2014) extend the scope of the analysis both considering more stress tests procedures (all the ones performed between 2009 and 2013) and checking whether the information provided affected the systematic and systemic risk. They first confirm the results obtained by Morgan et al., but also propose new insights on SCAP impact on systematic risk. What they find is that the betas of the banks, subjected to the exam, were significantly affected registering an increase after the announcement and a subsequent slight decrease at the results disclosure. This leaves some uncertainty on the effective impact of the increase in transparency on the systematic risk.

Although the ability of such exercises to convey information to the public has already been proved, we deem important to highlight how this news affect the market perception and its behavior in the medium term. This is a crucial aspect, as there is no agreement in literature on the effect of an increase in transparency on the stability of financial system. On one hand, lies the claim that enhanced authorities' communication allows the market to better assess the situation of each bank and to single out the most distressed ones. In particular, according to Barlevy and Alvarez (2014), the disclosure plays a decisive role in smothering financial contagion as it helps to avoid market freezes and to distinguish between institutions hit by the adverse shock and the ones that are not. Nier (2005) claims that ex-ante transparency always curbs systemic risk increasing market control on banks while, after an adverse shock has hit the economy, it helps to distinguish between banks directly hit by it and those that have suffered the systemic contagion. As a consequence, a separating equilibrium is generated that allows players to discriminate good and bad institutions.

An opposite view is offered by Goldstein and Leitner (2015) who suggest that in ordinary times no disclosure is the best choice, because even partial one would impair the ability of institutions to undertake risk sharing practices, destabilizing the system. For the same reasoning, they claim that, in crisis time, partial disclosure would help preserve stability at the best. Another argument against full disclosure comes from Goldstein and Sapra (2013) who claim, in the spirit of Morris and Shin (2002), that, as the financial market is affected by strategic behaviors, the disclosure of public information may lead agents to undervalue fundamentals and give excessive importance to the general reaction. In the long run, this may push them to decrease their efforts in gathering private information lowering the informative content of market prices and impairing market discipline, especially if the news disclosed contain some noise. Cordella and Yeyati (1998) state that disclosure induces negative feedback on the probability of bank failure by allowing deposit rates to adjust to revised risk estimates when the banks cannot control the volatility of their exposure due to an exogenous risk source. Thus, the bank is "taxed" during hard times and "rewarded" during good times.

The possible "trait d'union" between those opposite views can be found in Spargoli (2013) who proposes a model showing that in crisis times, if the exercise is well designed and central banks can pose a credible recapitalization threat on banks, (as the Fed did in the SCAP through the Capital Assistance Program - CAP), then the disclosure generates a positive market reaction and hence provides a solid contribution in restoring confidence and reviving the economy. If such a backstop mechanism is not implemented, the information might not generate the wanted reaction, as happened in the European case.

In summary, from the debate we cannot infer a clear expected market reaction to such an unprecedented transparency shock as there is no agreement about whether it can have a quelling effect, smothering the turbulences brought by the exogenous shocks, or rather amplifying those disturbances exacerbating the already distressed financial environment.

3. Study Design

Despite a widespread agreement (Morgan et al., 2014; Steffen, 2014; Schuermann, 2014) on SCAP effective information contribution, its net effect on systematic risk of banks still remains opaque (Neretina et al., 2014) and further investigations are required to evaluate its ability to reduce the perceived riskiness of the overall system. To shed light on this critical point, we evaluate the ex-post effect of the US 2009 SCAP on market betas, as originally proposed by Neretina et al. (2014), who study how the market updated its expectations of the riskiness of the banks as a consequence of the new information set provided by the regulator adding to their study in two ways. Firstly, we run an analysis of the betas variation over time using a time varying parameters approach, a choice that frees us from selecting any *a priori* structural break. Indeed, even if we know some dates at which the market reacted strongly (as can be the so called *clarification date* and the *disclosure date*), we do not want to impose these dates as restrictions on our model. In other words, we want the model to “find” them by inferring regime changes through the data, if any.

Secondly, we estimate how long the release of new information affects the market through a learning algorithm.

Amongst the different models[2] available to address such issues (Das and Ghoshal, 2010), we decide to develop a state-space representation of the Fama and French (1993) 3FM, estimated with a Kalman filter, henceforth KF (Kalman, 1960): doing this, we are able to implement a time varying parameters model that takes into account the need of the learning mechanism above indicated. The signal equation is specified as a Fama-French 3FM as it properly takes into account the trade-off between the simplicity of the model and its explanatory power.

3.1 Model Development

State-space models include a wide variety of specifications, which has proved to be useful in the time series analysis (Durbin and Koopman, 2012; Hamilton, 1994; Aoki, 2013).

For each multivariate time series it is possible to write their general *state-space* form, made by the *signal equation* (or *measurement equation*) and the *state equation* (or *transition equation*). As defined by Harvey (1989), those representations can be interpreted as regression models with time series data as explanatory variables which parameters can be shaped as time-varying processes; once a model has been set in this form, it is possible to apply known algorithms such as the KF[3] that recursively estimate the optimal parameter of the state vector at each moment.

The analyses are carried out with Matlab R2014b using the SSM toolbox by Peng and Aston (2011).

For the *i-th* security, we estimate the following model:

$$\begin{aligned} \mathrm{R_{i,t}} &= \mathrm{Z_t}\beta_{\mathrm{i,t}} + \epsilon_{\mathrm{i,t}}\ ,\ \epsilon_{\mathrm{i,t}} \sim \mathrm{GED}(0, \mathrm{H_t}) \\ \beta_{\mathrm{i,t+1}} &= \mathrm{T_t}\beta_{\mathrm{i,t}} + \mathrm{D_t}\eta_{\mathrm{i,t}}\ ,\ \eta_{\mathrm{i,t}} \sim \mathrm{N}(0, \mathrm{Q_t}) \\ \beta_{\mathrm{i,1}} &\sim \mathrm{N}(\mathrm{b}_{\mathbf{i,1}}, \mathrm{P}_{\mathbf{i,1}}) \end{aligned} \tag{1}$$

where:

- *t* is the sample extension, equal to 1303;
- $R_{i,t}$ is the excess return vector of the *i-th* asset. Before computing returns, we adjusted security prices for dividends and stock splits.;
- Z_t = [1 mkt smb hml 0 0 0 0] is the state to observation transform matrix, of dimensions [8 × 1303]. It is composed of a ones-vector (the constant of the 3FM), the 3 FF factors - market minus risk-free rate[4] (*mkt*), small minus big (*smb*), high minus low (*hml*) - and four zero-vectors[5].
- $\beta_{i,t}$ is the state sequence. It is the matrix of time-varying betas composed of 8 vector: the first four betas are the time-varying parameters of the 3FM, while the last four model the impact of the business cycle over the previous ones[6]. As we do not hold any clear *a priori* knowledge about the mean state (and its variance) about the estimated coefficients with the KF, we let the model to operate with diffuse initial priors.
- T_t is the state update transform matrix, a 3D array of dimensions [8×8×1303], which form in the generic *t-th* period is:

$$\mathrm{T_t} = \begin{bmatrix} 1 & 0 & 0 & 0 & cycle_t & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & cycle_t & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & cycle_t & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & cycle_t \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Setting equal to 1 the elements on the principal diagonal we allow the coefficients to be autoregressive and time-varying; moreover, putting into the T array a proxy for the business cycle enables the model to estimate its impact on each of the 3 FF factors and the constant term.

Doing so, we are able to separate the portion of variation estimated in betas derived from the business cycle from that due to changes in the industry riskiness ($\eta_{i,t}$); as proxy indicator of the business cycle, we use the 3m T-bill rate[7] (Tainer, 2006), henceforth 3mTbr[8]. We choose to isolate the business cycle effect as it represents a main determinant of the betas movements identifying any break in their pattern that is not cycle-driven. We do not have to handle multicollinearity between such variable and the risk free rate, as they enter in different levels: the risk free rate which is the 1m T-bill return, is just used to compute the excess returns hence it appears only in the signal equation; contrarily, the business cycle, proxied by the 3mTbr, merely loads the betas at the lower level of the state equations.

- D_t is the state disturbance transform matrix, an [8 × 8 × 1303] diagonal array that is useful to model as cross-independent the error terms of the *transition equations*.
- $\varepsilon_{i,t}$ is the observation disturbance vector, with dimension [1×1303], representing the error term of our dynamic 3FM.
- $\eta_{i,t}$ is the state disturbance vector. It is an [8 × 1303] array; since we control for the business cycle, each error term represents the update of each beta solely determined by changes in the riskiness.
- H_t and Q_t arrays are [1 × 1 × 1303] and [8 × 8 × 1303], respectively: H_t measures the variance of the GED distribution, while the Q_t is a static identity array.

As many financial time series do not follow Normal distributions, showing both Kurtosis and Skewness issues (see for example Corrado and Su, 1997; Mittnik and Paolella, 2003), we update our model[9] relaxing the Normality hypothesis and hence modelling error terms as General Error Distribution (henceforth GED) noise (see Nelson, 1991; Andersen, 1996). In this way, we allow for the possibility of fat-tailed and uncentered residuals which can be modelled by GED that are robust to the presence of outliers thanks to their adaptive tails (Azzalini, 2013). Furthermore, we do not make any assumption about tail behaviors, leaving them subject to model inference (Fioruci et al., 2014).

The SSM toolbox allows to model the error distribution as GED coupling it with a dynamic component estimation of a state space model. Particularly, the non-Gaussian estimation are approximated as dynamic Gaussian noise with dynamic variances thus, enabling the application of the KF.

The necessity of taking into account the business cycle forces us to improve the general state-space model introducing two innovations.

The first one is related to the model specification and hence the estimation procedure so that time series of betas take in account the impact of the business cycle. It is possible to consider the effect of the business cycle modelling it as a factor of the Z_t matrix; however, such adjustment to the general state-space form is useful to estimate the impact of the business cycle directly on the returns. A more refined approach would be to model it with a dynamic β_t, in order to account for the variability of the business cycle impact.

We further innovate this last approach by putting the business cycle proxy directly inside the T_t matrix thus relaxing the hypothesis that the business cycle has the same (whether or not static or dynamic) impact over the model factors; in other words, as explained above, the model is now able to estimate also others four time varying parameters β_t for the business cycle over each one of the coefficients of the 3FM hence, obtaining more accurate estimates.

The second improvement, presented in the next sub-section, is solely algebraic and is necessary to reconstruct the de-cycled time series of betas.

3.2 "De-cycling" betas

Once that betas are estimated using the previously reported model, we refine them to purge, or better take into account, the effect of the business cycle. In other words, we do not want our betas to be influenced by the overall economic conditions thus isolating the risk component unaffected by the general market situation (see for example Ang and Chen, 2002; Longin and Solnik, 2001).

Doing this, we present a second methodological innovation to conventional state-space forms.

In particular, KF estimates are influenced by the business cycle, which impact on the three FF factors is measured by the last four betas of the state sequence. We therefore compute the variation of the betas only due to changes in riskiness by implementing the two steps procedure described by the equations (2) and (3).

$$\eta_{\mathrm{i,t}} = \widehat{\beta}_{\mathrm{i,t+1}} - \widehat{\beta}_{\mathrm{i,t}} - \widehat{\beta}_{\mathrm{i,t}}^{cycle} \cdot \mathrm{3mTbr_t} \tag{2}$$

$$\widetilde{\beta}_{\mathrm{i,t+1}} = \begin{cases} \widehat{\beta}_{\mathrm{i,t+1}} & \text{if } \mathrm{t} = 0 \\ \widetilde{\beta}_{\mathrm{i,t}} + \eta_{\mathrm{i,t}} & \text{if } \mathrm{t} > 0 \end{cases} \tag{3}$$

The equation (2) disentangles the error terms $\eta_{i,t}$ from the mean state for each period, that is the update of market betas unrelated with the business cycle[10].

The time series of de-cycled updates (that is, betas updates not related to the business cycle) allows us to implement the second step of our procedure recursively adding to the initial betas the updates occurred in each period.

Thanks to this second innovation, our de-cycled market betas (represented by the β-tilde in the equation (3)) are free from the impact of the economic cycle; in other words, changes in these time series are not due to changes in macroeconomic conditions, allowing us to evaluate how the market processed the new information set provided through the SCAP to update its risk assessment of banks.

However, this adjustment also leads to the caveat that readers should not interpret the newly estimated betas using the canonical thresholds. With regard to their expected patterns, we do not have any a priori knowledge about the market reaction to SCAP disclosure for both the industry beta and the single banks ones. If we spouse Barlevy and Alvarez (2014) and Nier (2005) claims, we should expect agents to interpret such a transparency enhancement as a risk-curbing factor while, according to Goldstein and Sapra (2013), Cordella and Yeyati (1998), Goldstein and Leitner (2015), we should see an increase in the market turbulence.

For what concerns the changes of risk perception, according to the existing literature we should expect that an increase in transparency enhances publics ability to distinguish between good and bad banks. This may bring to a separating equilibrium where the public lowers its risk assessment about the well-performing banks while increasing it in relation to the poor-performing ones. Conversely, it can lead to two opposite corner solutions: the first would see the public augment its fear of a systemic collapse, panicking as it observes some banks not meeting the capital threshold, hence revising up its risk valuation for everyone; alternatively, a second hypothesis would see agents perceive a riskiness decrease for both passed and failed institutions due to a new-found trust towards the central banks commitment to guarantee their recapitalization. This can induce them to think that the system will come out sounder from such a test.

4. Data Collection

We focus our analysis on the US 2009 SCAP as it is the only macroprudential practice that proved to be useful in conveying new information to the market and to which many pundits attributed part of the merit of the restart of the whole economy (Morgan et al., 2014; Bernanke et al., 2010).

Our model is estimated on two different samples. The first one, which we also refer to as *bank sample,* is composed of 18 out of the 19 US banks under the FED assessment analysed on individual basis: GMAC (Ally Financial Services) is excluded since it was not publicly traded during the period analysis. The second sample is composed of the following 10 GICS industry indexes: Consumer Discretionary, Consumer Staples, Energy, Financials, Healthcare, Industrials, InfoTech, Materials, Telecommunication Services, Utilities. Henceforth, we call this sample as *index sample*[11].

Furthermore, we consider the scap portfolio (henceforth Pscap) which includes the 18 traded banks participating to the exercise.

Index prices, as well as bank quotes and Pscap returns, are taken from Bloomberg whereas the 3FF factors are downloaded from the Professor Kenneth French website. The estimation sample covers 25 years, ranging from January 1st 1990 to December 31st 2014, with all but four banks registering 1303 observations: Morgan Stanley (listed and publicly traded from February 23, 1993), Capital One Financial (which starts from November 11, 1994), Goldman Sachs (listed on May 3, 1999) and Metlife (which starts from April 4, 2000).

We use weekly returns as they enable us to properly take into account the business cycle and do not contain too much noise when compared to the daily returns (Akgiray and Booth, 1988).

Table 1 shows some characteristics of the 18 banks considered in our analysis with panel A showing the values for each bank and Panel B showing the main summary statistics:

Table 1: Banks main characteristics as of 12/31/2008 (USD Billion)

Panel A[a]						
Bank	**Market Value**	**Total Assets**	**Tier Capital**	**Leverage**	**RWAs**	**GAP**
American Express	21.52	126.07	10.1	12.48	104.4	0
Bank Of America	70.65	1,817.94	173.2	10.5	1,633.80	33.9
Bank Of New York Mellon	32.54	237.51	15.4	15.42	115.8	0
Bb&T	15.36	152.02	13.4	11.34	109.8	0
Capital One Financial	12.49	165.91	16.8	9.88	131.8	0
Citigroup	36.57	1,938.47	118.8	16.32	996.2	5.5
Fifth Third Bancorp	4.77	119.76	11.9	10.06	112.6	1.1
Goldman Sachs	38.34	884.55	55.9	15.82	172.7	0
JP Morgan Chase	117.7	2,175.05	136.2	15.97	1,337.50	0
Keycorp	4.22	104.53	11.6	9.01	106.7	1.8
Metlife	27.67	501.68	30.1	16.67	326.4	0
Morgan Stanley	15.45	658.81	47.2	13.96	310.6	1.8
Pnc Financial Services	21.71	291.08	24.1	12.08	250.9	0.6
Regions Financial	5.5	146.25	12.1	12.09	116.3	2.5
State Street	16.97	173.63	14.1	12.31	69.6	0
SunTrust Banks	10.47	189.14	17.6	10.75	162	2.2
Us Bancorp	43.89	265.91	24.4	10.9	230.6	0
Wells Fargo	124.66	1,309.64	86.4	15.16	1,082.30	13.7
Panel B[b]						
Statistics	**Market Value**	**Total Assets**	**Tier Capital**	**Leverage**	**RWAs**	**GAP**
Sum	620.48	11,257.95	819.3	230.72	7,370.00	63.1
Mean	34.47	625.44	45.52	12.82	409.44	3.51
Standard Deviation	35.64	699.85	49.71	2.51	489.64	8.28
Minimum	4.22	104.53	10.1	9.01	69.6	0
Median	21.62	251.71	20.85	12.2	167.35	0.3
Maximum	124.66	2,175.05	173.2	16.67	1,633.80	33.9

The table shows markets values, total assets, Tier 1 capital, Leverage (total assets over Tier 1 capital), Risk Weighted Assets, and the capital shortage resulted from the SCAP (GAP) for the 18 sufficiently traded banks under the FED assessment; Panel B provide further information about each variable on aggregate basis.
Source:
a - Fed (2009)
b - Our elaboration from Fed (2009)

Our sample covers 98.34% of the assets scrutinised under the SCAP resulting in a total asset of more than 11 trillion. In order to understand how systemically important are the 18 banks composing our sample, one should consider that the smallest one, Keycorp with 104.53 billions of total assets, has more than 4 billions of market capitalization.

The average bank, exposed for 409.44 billion, has a Tier 1 capital of almost 13 billion and about 92% of debt-financed business. The SCAP resulted into a capital shortage of 63.1 USD billions, ranging from zero (situation shared by half banks of the sample) to the 33.9 billions of Bank of America. In terms of total assets, the total Gap, emerged from this exercise, accounts for 0.56%.

Table 2 shows the descriptive statistics of all the excess returns useful to implement our model.

Table 2: Samples returns descriptive statistics

Panel A[a]								
Bank	**N**	**μ**	**σ**	**Min**	**Med**	**Max**	**Skew**	**Kurt**
American Express	1303	0.23%	4.63%	-26.92%	0.08%	27.58%	0.09	4.97
Bank Of America	1303	0.15%	6.09%	-44.73%	0.15%	83.44%	2.45	41.86
Bank Of New York Mellon	1303	0.20%	4.61%	-21.85%	0.15%	29.69%	0.33	3.54
Bb&T	1303	0.15%	4.08%	-19.36%	0.05%	25.85%	0.53	4.9
Capital One Financial	1049	0.43%	6.95%	-31.67%	0.18%	80.74%	1.91	21.48
Citigroup	1303	0.24%	7.09%	-60.41%	0.03%	119.89%	3.93	78.91
Fifth Third Bancorp	1303	0.27%	7.12%	-48.50%	-0.04%	120.52%	5.85	103.97
Goldman Sachs	816	0.22%	5.44%	-30.65%	0.35%	48.16%	0.99	11.34
JP Morgan Chase	1303	0.22%	5.40%	-34.09%	0.21%	49.09%	0.74	10.24
Keycorp	1303	0.12%	5.32%	-45.92%	0.11%	49.59%	0.76	21.84
Metlife	768	0.29%	5.76%	-34.34%	0.10%	55.62%	1.28	21.03
Morgan Stanley	1139	0.33%	6.97%	-59.55%	0.07%	98.74%	2.49	43.2
Pnc Financial Services	1303	0.16%	4.82%	-32.30%	0.02%	52.08%	1.09	18.31
Regions Financial	1303	0.14%	5.82%	-32.42%	0.09%	69.34%	2.76	36.38
State Street	1303	0.28%	5.08%	-46.63%	0.12%	32.50%	0.01	11.25
SunTrust Banks	1303	0.18%	5.45%	-33.38%	0.14%	63.67%	1.73	27.3
Us Bancorp	1303	0.28%	4.77%	-38.37%	0.20%	53.85%	1.18	20.62
Wells Fargo	1303	0.29%	4.86%	-30.78%	0.19%	61.90%	1.98	29.84
Pscap	1303	0.23%	4.23%	-25.03%	0.25%	44.41%	1.49	22.26
Panel B[b]								
Index	**N**	**μ**	**σ**	**Min**	**Med**	**Max**	**Skew**	**Kurt**
Consumer Discretionary	1303	0.13%	2.77%	-18.30%	0.19%	17.06%	-0.09	5.01
Consumer Staples	1303	0.12%	2.02%	-15.96%	0.17%	10.86%	-0.53	5.88
Energy	1303	0.13%	3.00%	-25.05%	0.20%	12.99%	-0.63	5.14
Financials	1303	0.12%	3.66%	-23.71%	0.12%	33.85%	0.72	14.28
Health Care	1303	0.15%	2.47%	-18.45%	0.13%	9.54%	-0.39	4.07
Industrials	1303	0.12%	2.67%	-17.48%	0.23%	12.40%	-0.23	3.82
Information Technology	1303	0.18%	3.57%	-21.61%	0.27%	15.60%	-0.3	2.59
Materials	1303	0.09%	3.02%	-15.35%	0.18%	15.15%	-0.16	3.16
Telecommunication Services	1303	0.01%	2.74%	-19.62%	0.07%	16.04%	-0.1	4.6
Utilities	1303	0.03%	2.30%	-20.26%	0.07%	8.28%	-0.85	6.75
Panel C[c]								
Factor	**N**	**μ**	**σ**	**Min**	**Med**	**Max**	**Skew**	**Kurt**
Mkt	1303	0.15%	2.35%	-18.00%	0.26%	12.61%	-0.53	5.85
Smb	1303	0.03%	1.36%	-10.31%	0.06%	6.73%	-0.43	6.42
Hml	1303	0.06%	1.38%	-7.54%	0.01%	10.59%	0.46	6.94
3m T-bill rate	1303	3.09%	2.32%	-0.01%	3.25%	8.23%	0.03	-1.24

Table 2 shows the descriptive statistics of weekly excess returns for banks (Panel A) and indexes (Panel B), and the Fama-French Factors and our proxy for the business cycle (Panel C).
Source:
a - Our elaboration of Bloomberg prices;
b - Our elaboration of Professor Kenneth French Data Library
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Panel A only refers to the bank sample and the Pscap. The average (median) return over 25 years from 1990 is 0.23% (0.25%) as emerges from Pscap, with banks average (median) return ranging from 0.12% of Keycorp (-0.04% of Fifth Third Bancorp) to 0.43% of Capital One Financial (0.35% of Goldman Sachs).

As for the individual's standard deviation, it ranges from a minimum of 4.08% (Bb&T) to a maximum of 7.12% (Fifth Third Bancorp) with the one of the portfolio equal to 4.23%. All banks, as well as the portfolio, are right-skewed and leptokurtic. The ten GICS sectors, which descriptive statistics are exposed in Panel B, show some differences in their returns distribution: on average (0.11%), the ten sectors performed worse than banks; however, these minor returns are combined with lower values of standard deviations (on average 2.82% versus 5.57% for banks). Moreover, all distribution but financials, are left-skewed with values of Skewness never less than -0.85 (Utilities sector).

Finally, Panel C of Table 2 refers to the 3FF factors, the risk-free rate and the US 3 months T-bill rate. The mean (median) market excess return is 5 (about 4) and 2.5 (about 25) times greater than SMB and HML mean (median) excess returns respectively, and no factors follow a Normal distribution. The US 3m T-bill rate shows high mean and median values (3.09% and 3.25% respectively) mainly due to the presence of high returns for the first years of our samples.

5. Results

While our procedures always start from January 1, 1990 (later for those banks that have been listed successively), we analyze the betas patterns only for the period surrounding the Pscap exercise.

Figures 1 and 2 show the estimated market betas for Bank of America and Fifth Third Bancorp, two particulars cases that best explain the big scenario in the variations of the risk in all banks.

Figure 1: Market betas (esimated and de-cycled) of Bank of America

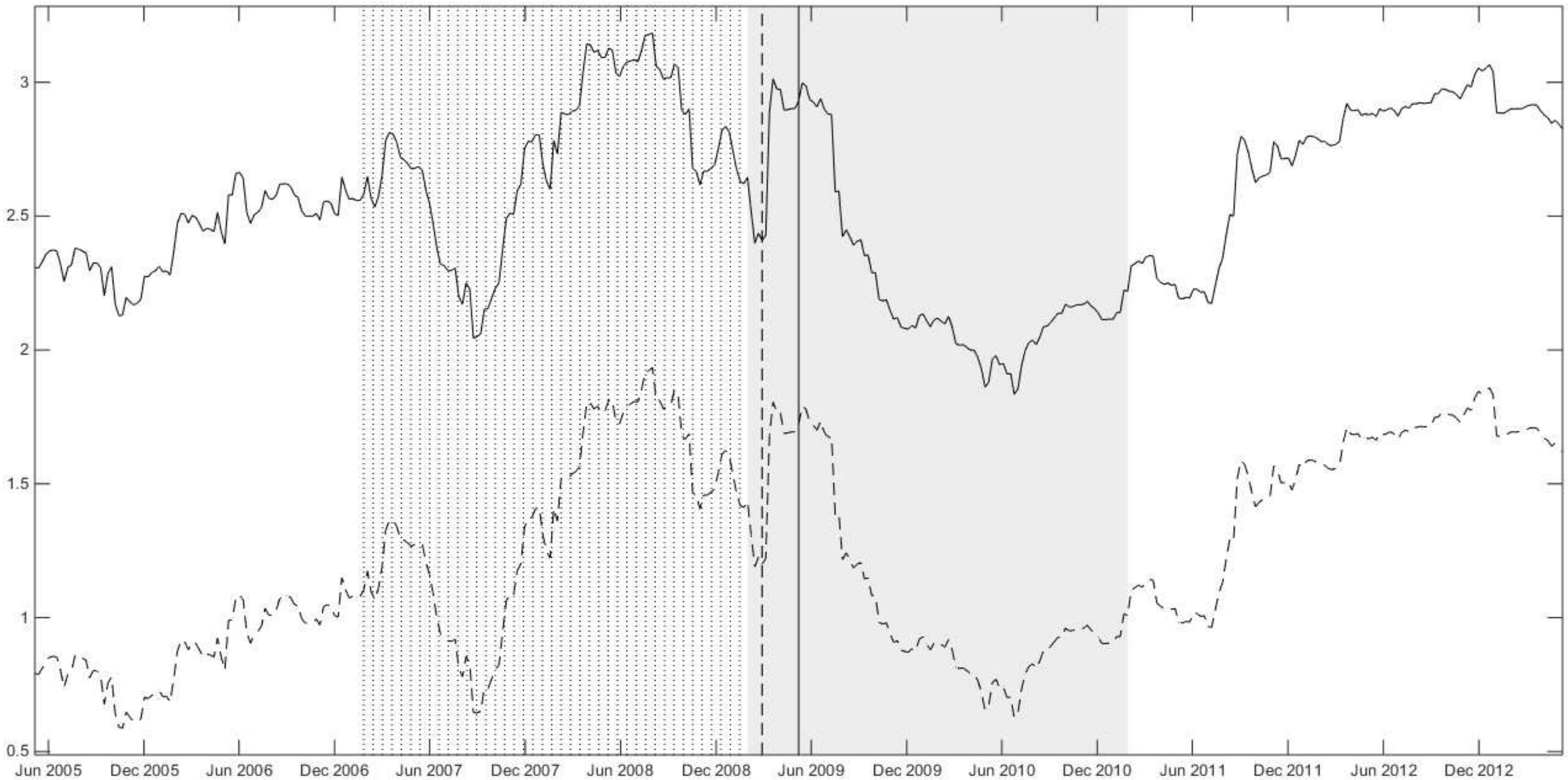

Figure 1 shows the estimated market betas (dashed line) and the de-cycled market betas (solid line) for Bank of America from 4 years before to 4 years after the SCAP. The dotted area and the shaded one represent the pre- SCAP period (January 26, 2007-January 23, 2009) and the post-SCAP period (January 30, 2009-January 28, 2011), respectively while, the dashed and solid vertical lines represent the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively.

Figure 2: Market betas (esimated and decycled) of FifthThird Bancorp

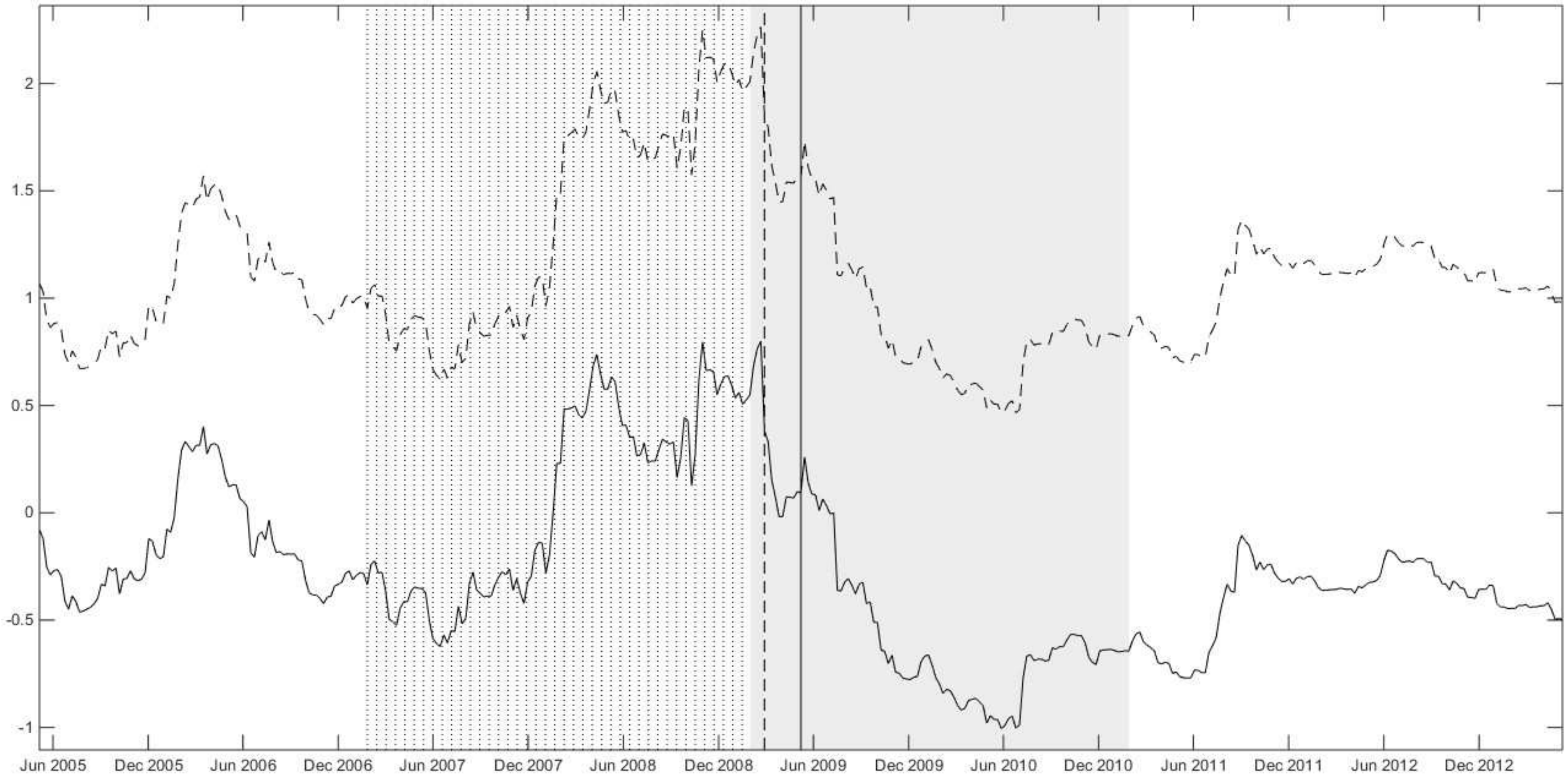

Figure 2 shows the estimated market betas (dashed line) and the de-cycled market betas (solid line) for FifthThird Bancorp from 4 years before to 4 years after the SCAP. The dotted area and the shaded one represent the pre- SCAP period (January 26, 2007-January 23, 2009) and the post-SCAP period (January 30, 2009-January 28, 2011), respectively while, the dashed and solid vertical lines represent the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively.

The dashed and solid lines represent the market and the de-cycled betas, respectively. Even if it may seem so, the reader should recall that the latter is not simply a translation of the former, that is to say, the distance between them is far from being constant. In order to simplify the interpretation of the graphs, we highlight two subsets: the dotted area, from January 26, 2007 to January 23, 2009 (henceforth indicated as pre-SCAP sample/period), and the shaded area, from January 30, 2009 to January 28, 2011 (henceforth post-SCAP sample/period). The *clarification date* and the *disclosure date* represented by the dashed and solid vertical lines respectively, fall into the post-SCAP sample hence allowing for news leakages and market anticipation.

Since the de-cycled betas is obtained through an auto recursive procedure, the impact of the business cycle is not always the same: in some cases the cleaning process, as for the Bank of America, causes an increase in the market betas whereas in others ones, such as Fifth Third Bancorp, it determines a decrease in the risk indicator even below the zero level, where a countercyclical institution is not detectable. For the same reason, a de-cycled beta between 0 and 1 does not necessarily indicate an institution less volatile than the market.

Such upward and downward shifts caused by the process used to control for the cycle, avoid us from interpreting the levels of the market betas that is to say, rather than looking at their levels, it is more useful to observe their variation which are expressions of changes in riskiness independently from the business cycle.

Abstracting from peculiarities, the two de-cycled betas reveal the same pattern: they first increase during the pre-SCAP period, for then experiencing a sharp decline during the post-SCAP period, especially after the *disclosure date*. Indeed, no clear pattern can be inferred from the analysis of banks betas immediately after the clarification date. This emerges more clearly from the analysis of Figures 3 and 4 that show the results for all banks, only focusing on the pre-SCAP (white area) and the post-SCAP period (shaded area).

Figure 3: Market betas (esimated and de-cycled) for the bank sample

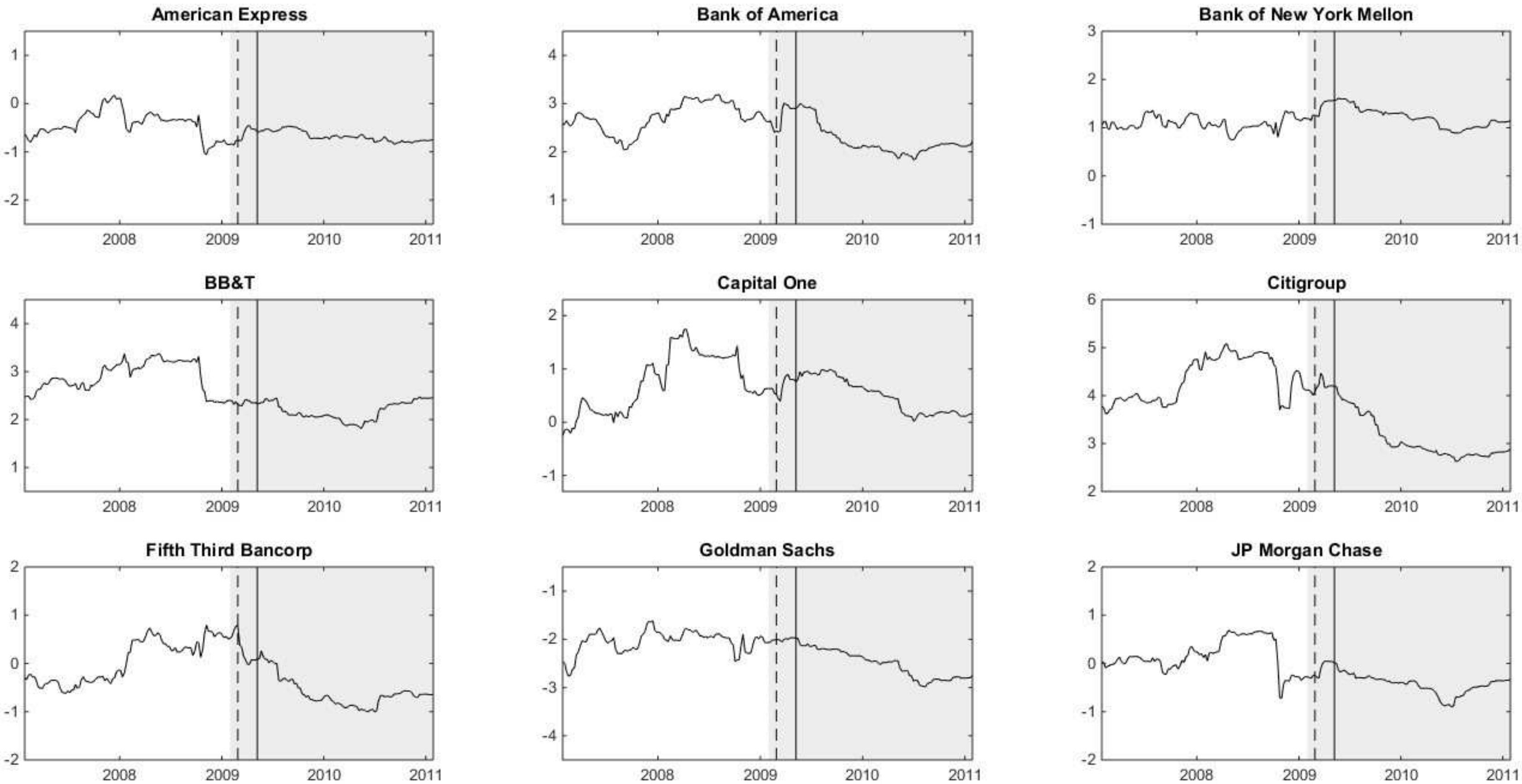

Figure 3 shows the de-cycled market betas (solid line) for the first nine banks of the bank sample, focusing on the pre-SCAP period (January 26, 2007-January 23, 2009) and the post-SCAP period (shaded area - from January 30, 2009 to January 28, 2011), with the dashed and solid vertical lines representing the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively.

Figure 4: Market betas (esimated and de-cycled) for the bank sample

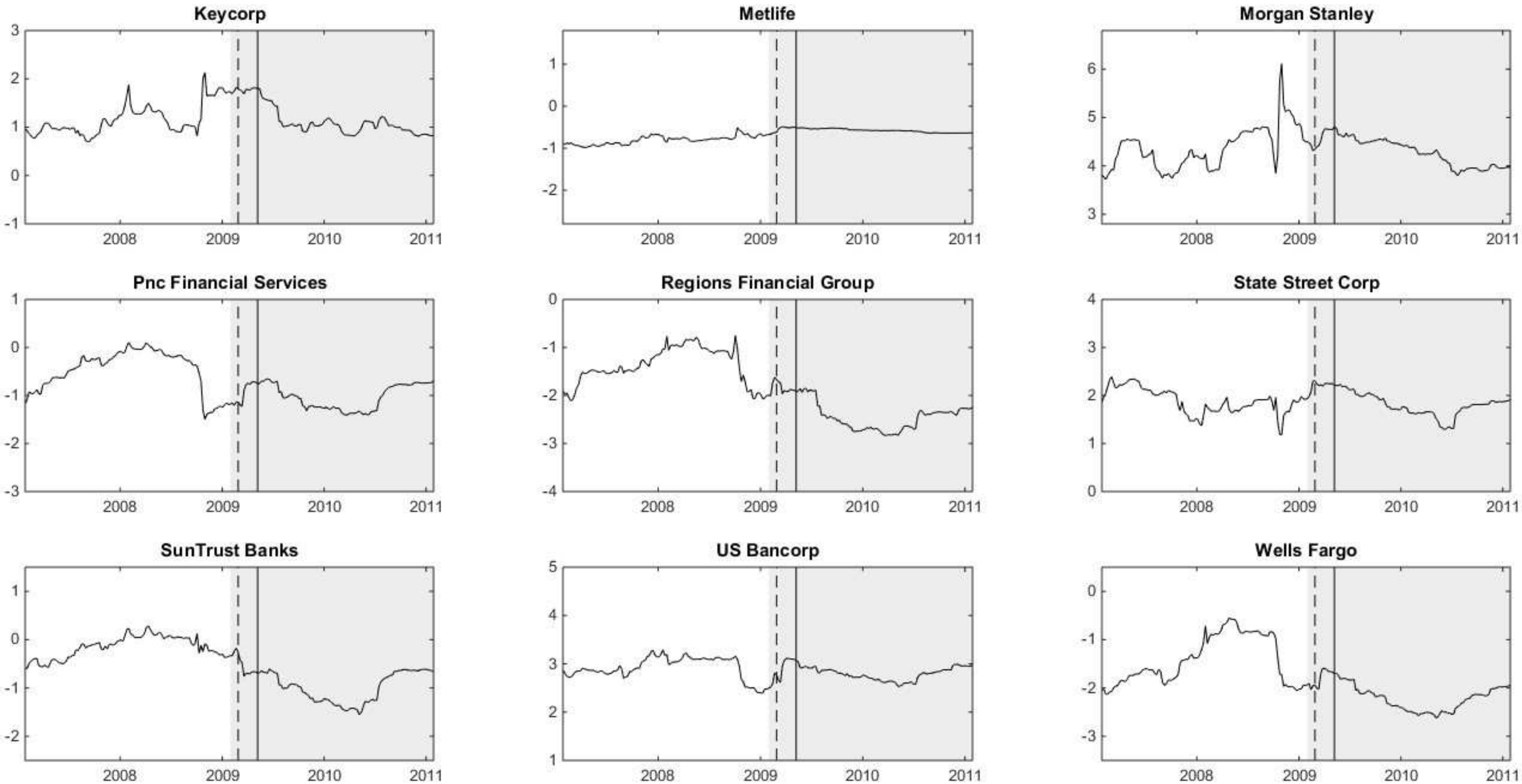

Figure 4 shows the de-cycled market betas (solid line) for the second nine banks of the bank sample, focusing on the pre-SCAP period (January 26, 2007-January 23, 2009) and the post-SCAP period (shaded area - from January 30, 2009 to January 28, 2011), with the dashed and solid vertical lines representing the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively.

In an attempt to simplify the graph, we only plot the de-cycled series of betas with the dashed and solid vertical lines representing once again the *clarification date* and the *disclosure date* respectively. While the vast majority of banks improves their riskiness after the *clarification date*, the adjustment process of the market starts immediately as results are disclosed. Moreover, the only two institutions which risk appears to remain constant, American Express and Metlife, registered no GAP that is to say, they passed the exam (see Table 1).

5.1 Time-Varying Betas

We refine our analysis to strengthen our results focusing on the period ranging from March 6, 2009 to September 7, 2010 (which we refer as *start date* and *end date* respectively): we consider market betas from the two months ahead the release of SCAP results, thus allowing for news leakages, to around a year after, in order to both measure the length of the market reactions and allow for anticipated and/or late responses. Results are reported in Table 3.

Table 3: Banks market betas evolution over time

Bank	Start Value	End Value	σ	Min Date	Min	Max	Max Date
American Express	-0.77	-0.79	0.1	07/02/2010	-0.81	-0.46	07/02/2010
Bank of America	2.41	1.85	0.38	07/02/2010	1.83	3.01	07/02/2010
Bank of New York Mellon	1.25	0.9	0.19	07/02/2010	0.9	1.62	07/02/2010
BB&T	2.3	1.96	0.18	05/14/10	1.81	2.45	05/14/10
Capital One	0.44	0.05	0.27	07/02/2010	0.02	0.99	07/02/2010
Citigroup	4.17	2.72	0.54	07/09/2010	2.72	4.47	07/09/2010
Fifth Third Bancorp	0.38	-0.99	0.42	06/04/2010	-1	0.38	06/04/2010
Goldman Sachs	-2.01	-2.85	0.23	07/02/2010	-2.87	-1.97	07/02/2010
JP Morgan Chase	-0.28	-0.88	0.24	07/02/2010	-0.91	0.05	07/02/2010
Keycorp	1.77	0.99	0.32	04/16/10	0.82	1.81	04/16/10
Metlife	-0.54	-0.6	0.03	07/02/2010	-0.6	-0.49	07/02/2010
Morgan Stanley	4.39	3.9	0.2	07/02/2010	3.88	4.81	07/02/2010
Pnc Financial Services	-1.19	-1.31	0.25	03/19/10	-1.41	-0.65	03/19/10
Regions Financial Group	-1.72	-2.69	0.37	05/07/2010	-2.83	-1.72	05/07/2010
State Street Corp	2.25	1.31	0.3	06/04/2010	1.29	2.25	06/04/2010
SunTrust Banks	-0.43	-1.25	0.31	05/07/2010	-1.55	-0.43	05/07/2010
US Bancorp	2.66	2.58	0.16	05/07/2010	2.53	3.11	05/07/2010
Wells Fargo	-2.01	-2.54	0.32	05/07/2010	-2.62	-1.59	05/07/2010
Pscap	0.8	0.05	0.3	07/02/2010	0.03	0.97	07/02/2010

Table 3 shows the evolution of banks market betas over time, reporting starting and ending values corresponding to March 6, 2009 and September 7, 2010, respectively, the standard deviation (σ) and the minimum and maximum values along with their corresponding dates. As reported betas take into account the business cycle, they must not be evaluated using the canonical thresholds (for example beta lower than zero does not identify countercyclical institution).

As almost all banks show the same trend for the market beta, we limit our analysis to the shared pattern and to any difference from the standard behavior.

Any misalignment between the peak and the release date is interpreted as a consequence of either the estimation procedure which may need few observations to absorb the new dynamic and invert the trend, or to the market participants, that may need some time to process the new information and revise their banks risk assessment.

Having abandoned the Normality assumption, we can neither rely on orthodox residual assumptions, nor univocally compute and test *P-scores* (Frühwirth-Schnatter, 1996) to test our non-Gaussian state space model. Thus, we conduct a peculiar analysis to investigate the presence of significant changes in the market betas regimes and the results are shown in Table 4.

Table 4: T-tests for differences and bootstrapped t-tests for the 18 banks and Pscap

Bank	**Pre SCAP Mean**	**Post SCAP Mean**	**Difference**	**t-test**	**Bootstrapped t-test Simulation**		
					1% cl	**5% cl**	**10% cl**
American Express	-0.42	-0.68	-0.26***	9	100%	100%	100%
Bank of America	2.72	2.29	-0.43***	9.8	100%	100%	100%
Bank of New York Mellon	1.09	1.23	0.14***	-5.91	100%	100%	100%
BB&T	2.9	2.2	-0.69***	19.28	100%	100%	100%
Capital One	0.74	0.52	-0.22***	3.54	83%	94%	97%
Citigroup	4.33	3.23	-1.10***	15.65	100%	100%	100%
Fifth Third Bancorp	0.04	-0.48	-0.52***	8.58	100%	100%	100%
Goldman Sachs	-2.05	-2.45	-0.40***	10.37	100%	100%	100%
JP Morgan Chase	0.16	-0.39	-0.56***	14.32	100%	100%	100%
Keycorp	1.16	1.16	0	0	1%	5%	10%
Metlife	-0.8	-0.58	0.23***	-21	100%	100%	100%
Morgan Stanley	4.37	4.3	-0.06	1.25	8%	23%	34%
Pnc Financial Services	-0.47	-1.02	-0.55***	11.3	100%	100%	100%
Regions Financial Group	-1.38	-2.37	-1.00***	20.32	100%	100%	100%
State Street Corp	1.88	1.85	-0.03	0.9	5%	15%	24%
SunTrust Banks	-0.15	-0.92	-0.77***	19.26	100%	100%	100%
US Bancorp	2.92	2.8	-0.12***	4.65	97%	99%	100%
Wells Fargo	-1.42	-2.17	-0.75***	13.47	100%	100%	100%
Pscap	0.95	0.48	-0.48***	14.35	100%	100%	100%

The table shows the de-cycled mean beta for the pre-SCAP period (from January 26, 2007 to January 23, 2009) and the post-SCAP period (from January 30, 2009 to January 28, 2011), respectively and their differences for the bank sample. Last columns report the t-test for the difference and the bootstrapped simulation of the t-test (that is, the rejection rate of null hypothesis of equal average) for the canonical confidence levels (cl) of 1%, 5%, and 10%, respectively. Since reported betas are de-cycled, their value must not be interpreted using the canonical thresholds: betas lower than zero do not identify countercyclical institution.

More precisely, we conduct t-tests for significant differences between the averages of the pre-SCAP and the post-SCAP samples: should the regime change of the market beta be effectively important (i.e. should the market value the information disclosed as important useful in changing its risk perception.), the average of the pre-SCAP and post-SCAP sample will be statistically different.

The average difference of the one-shot t-tests is -0.49 with a test significant on 15 out of 18 banks (14 at a 1% significance level, 1 at a 10% significance level) in the sample: only two banks recorded a positive difference but rather than suggesting some signaling values, they better confirm the emerging of a corner solution, as both do not have to raise additional capital.

However, as these t-tests could suffer from biased estimates, we bootstrap the two subsets, (50000 repetitions) for each market betas of the banks and conduct the same t-tests, with 3 different significance levels (the canonical thresholds of 10%, 5% and 1%). The last 3 columns of table 4 show the rejection rates of the null hypothesis (pre-SCAP average equals post-SCAP average): it can be seen that results largely support the evidence indicated by previous tests.

The risk reduction experienced by almost all banks seems to be in net contrast with the separating equilibrium proposed by Nier (2005) and Barlevy and Alvarez (2014): the reduction of information asymmetries appears to influence positively the risk perception even if it means to disclose bad news, as it is for banks that failed the exercise.

Several reasons may cause this intriguing corner solution. On the one hand, our results combined with the separating equilibrium on CARs at the *clarification date* and subsequent positive CARs on the release date only for suffering banks (Morgan et al., 2014) seem to suggest an update of expectations, which were too much severe because of information asymmetries: that is, the scarcity of knowledge lets the market to overestimate the banks riskiness, especially for the weaker ones. On the other hand, a corner solution can be due to a market reaction in line with the regulators intention of reducing systemic risk: through macroprudential practices, regulators first inform the market of eventual banks shortcomings and then they compel institutions to raise additional capital, reassuring the market on the overall soundness of the system.

Such news reduces per se the riskiness of the whole industry, thanks to the certainty that if banks were unable to provide for themselves, they would receive access to contingent common equity provided by the U.S. government as a bridge to private capital in the future, alike what the FED assured in the CAP white paper[12].

Having identified the betas pattern for each bank, we investigate if the reduction experienced by almost every bank leads to a decrease in systemic risk, which was the main goal of the macroprudential practices. The aim of the next section is to provide some insights with regard to this issue, thanks to the use of the *index sample*.

5.2 From Systematic to Systemic Risk: Has the Market Reduced its Overall Risk Perception?

The emerging of a corner solution imposes us to investigate the reason underlying it: even if it is not necessary to observe on the risk perception the same pattern highlighted on returns, it is still true that the risk reduction also for banks who failed the exercise is somewhat puzzling.

We investigate the commonalities and the differences between the ten GICS sectors, aiming at discovering if such a corner solution is due to a reduction in systematic risk, or in the systemic one. Indeed, being the market betas testimony of the former, the differences between each of the ten GICS industries represents the peculiar riskiness attributable to an industry, that is to say the systemic risk of each one of them.

Therefore, should the systematic risk decline, the betas of almost all the 10 industries may decrease; on the other hand, should only the (banking) systemic risk be affected, the beta of the banking industry may be bound to experience a behavior different from others.

Before analysing the estimated betas as we did for each bank, a graphical analysis may now help to understand any difference and/or similarity between the Pscap and other GICS industries. Thanks to their similarity (due to the fact that Pscap comprises the 18 larger US banks), we do not discuss the Financial sector index, thus focusing only on the Pscap.

Figure 5, 6 and 7 show the de-cycled time-varying market betas of Pscap (solid line) and time-varying market betas of the nine GICS sector (short-dashed line). We center the graph on May 2009 (release period of SCAP results), presenting the beta estimates for two years before and after it.

The choice of this left bound allows us to gain appreciable insights about the state of art of the various industries before the exercise, useful to make comparisons and evaluate the effects of the transparency shock, but also allows for the possibility of market anticipation of the SCAP results, henceforth named anticipation effect.

On the other hand, the right bound enables us to evaluate the effects of the exercise beyond the short-term, hence allowing for the possibility of delayed responses of the market (see for example MacKinlay, 1997).

Figure 5: Market betas (de-cycled) for Pscap and index sample

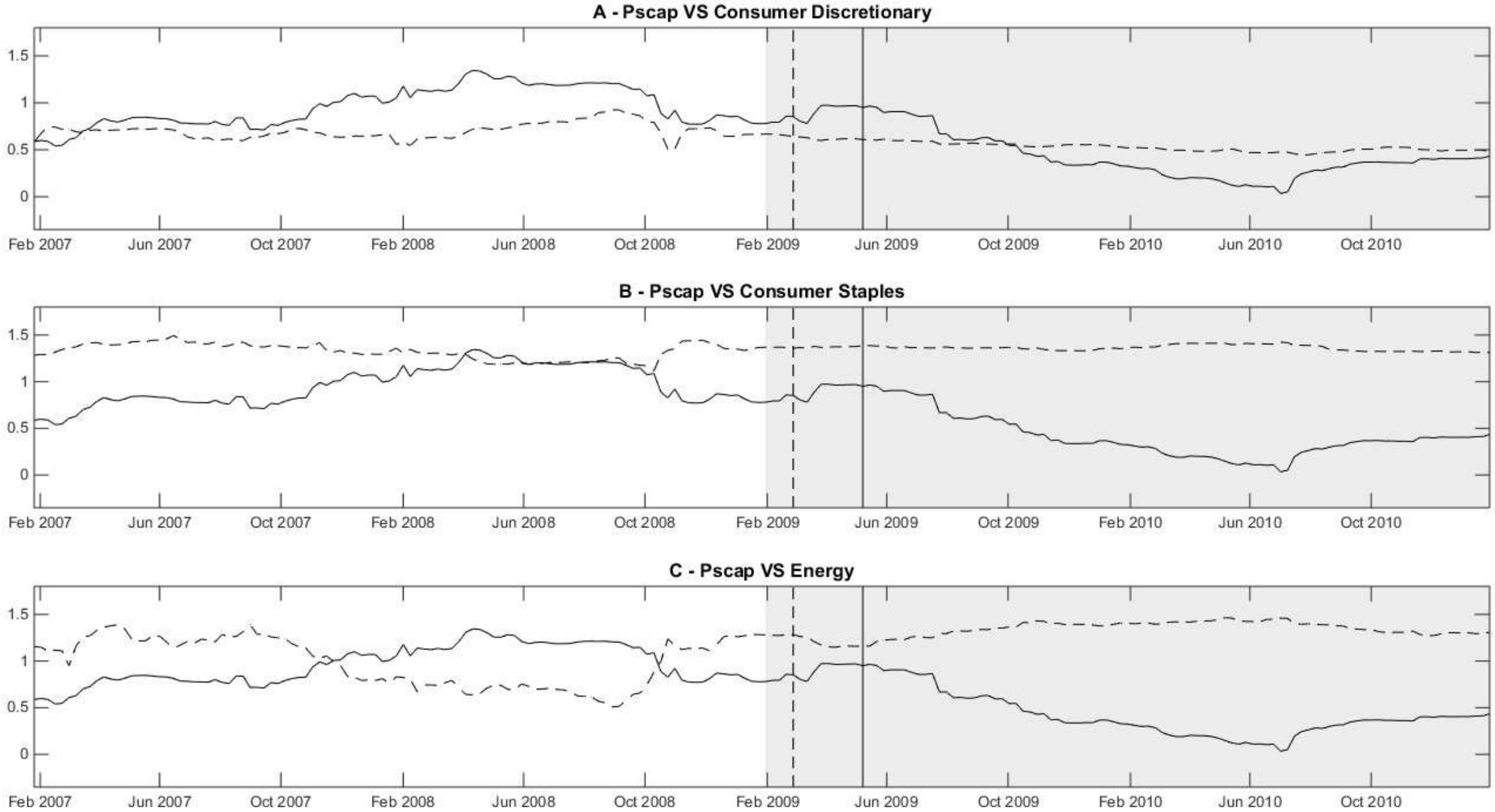

Figure 5 compares the de-cycled market betas of the Pscap (solid line) with repspect to the one of Consumer Discretionary (subplot A), Consumer Staples (subplot B) and Energy (subplot C), respectively the dashed lines of the three plots. The dashed and solid vertical lines represent the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively. Reported betas must not be interpreted using the canonical thresholds, as they are estimated in order to exclude the portion of variation due to the business cycle.

Figure 6: Market betas (de-cycled) for Pscap and index sample

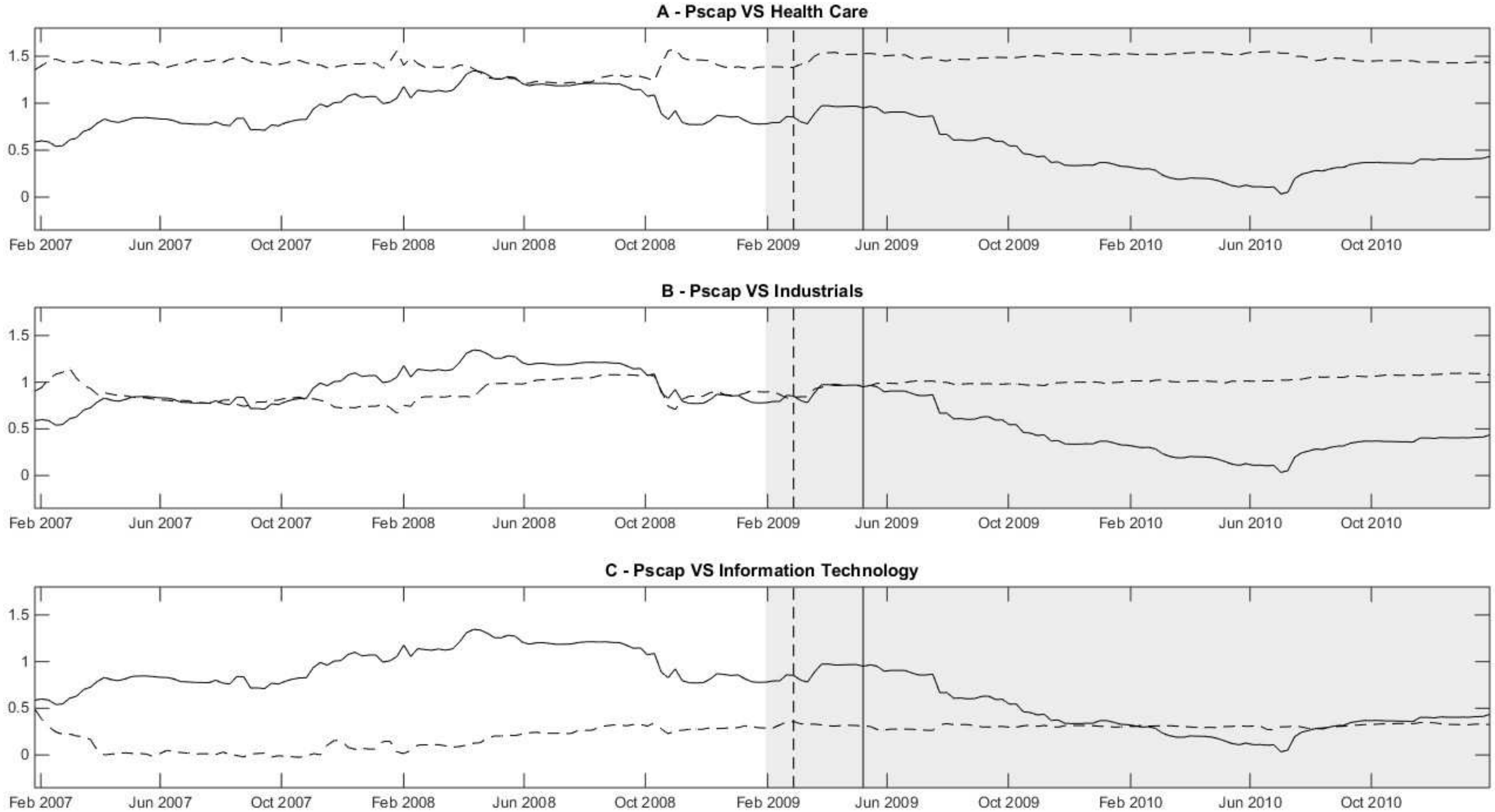

Figure 6 compares the de-cycled market betas of the Pscap (solid line) with repspect to the one of Health Care (subplot A), Industrials (subplot B) and Information Technology (subplot C), respectively the dashed lines of the three plots. The dashed and solid vertical lines represent the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively. Reported betas must not be interpreted using the canonical thresholds, as they are estimated in order to exclude the portion of variation due to the business cycle.

Figure 7: Market betas (de-cycled) for Pscap and index sample

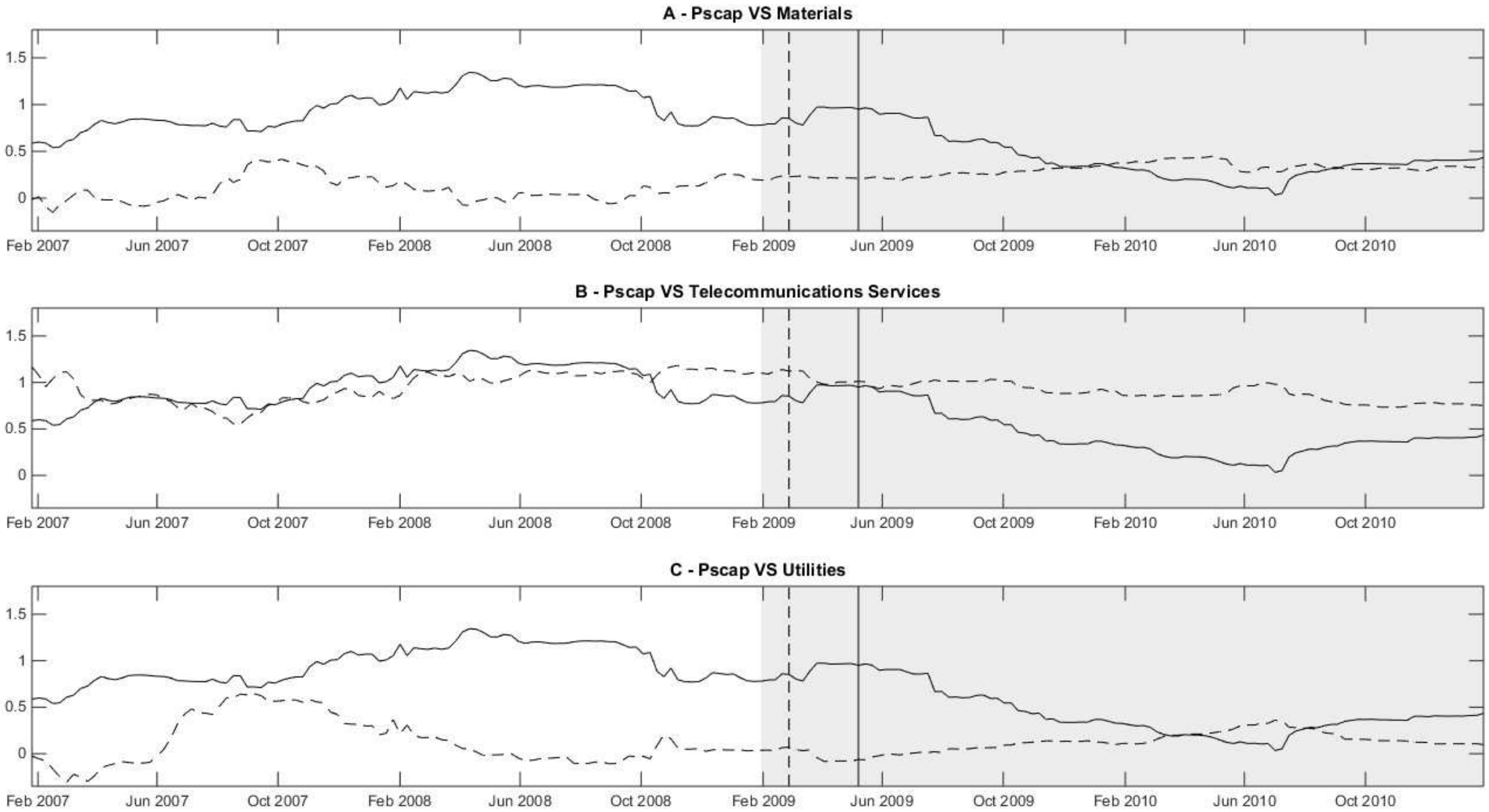

Figure 7 compares the de-cycled market betas of the Pscap (solid line) with repspect to the one of Materials (subplot A), Telecommunication Services (subplot B) and Utilities (subplot C), respectively the dashed lines of the three plots. The dashed and solid vertical lines represent the clarification date (February 23-25, 2009) and the disclosure date (May 7, 2009), respectively. Reported betas must not be interpreted using the canonical thresholds, as they are estimated in order to exclude the portion of variation due to the business cycle.

Taking a look to the three figures, one can observe that market betas of Pscap, compared to other industries, is the only one characterised by an appreciable decline. After reaching a peak between the clarification date and the release date of SCAP results, it constantly declines for about a year experiencing a reduction of more than the 96% (from about 0.97 to 0.03).

With regard to the same time-span, beside the Pscap and the Financial sector, only the Consumer Discretionary index apparently shows a similar co-movement. notwithstanding its pattern the market beta differs from the one of the Pscap in terms of both timing and magnitude of the decrease: while the latter starts to decline between the clarification and the disclosure date, almost decreasing by 100% (about -0.94 of absolute variation), the former declines sooner due to the presence of a decreasing trend (started in December 2008) and experience a reduction, in the Pscap reference period, of about 20% (only -0.13 in terms of absolute variation). Furthermore, other three indexes, Healthcare, Information Technology and Telecommunication Services, have negatively sloped betas. However, such indexes, whose relative variation just exceed 3% only for Information Technology, never show an absolute variation greater than 0.01.

All the other sectors do not exhibit a reduction in their market betas: indeed, three sectors (Energy, Materials and Utilities) augment their riskiness, as the values of the beta increase of about 27%, 32% and 543% respectively; finally, Consumer Staples and Industrials seem not to experience any relevant change in their riskiness, as their market betas remain almost the same over the considered period (+3.85% and +5.11%, respectively).

If we compare the Pscap and the other sectors using the t-test procedure above identified, results (as reported in Table 5) remain qualitatively similar: the Pscap showed almost 0.5 decrease from 0.95 to 0.48 (1% significance level), while the indexes showed mixed effects: almost all experience a positive or non-significant variation, thus confirming the increase, or the regularity, of the markets risk perception.

Table 5: T-tests for differences and bootstrapped t-tests for the 10 GICS sectors and Pscap

Index	Pre SCAP Mean	Post SCAP Mean	Difference	t-test	Bootstrapped t-test Simulation		
					1% CI	5% CI	10% CI
Consumer Discretionary	0.7	0.54	-0.16***	16.52	100%	100%	100%
Consumer Staples	1.33	1.36	0.04***	-4.21	96%	99%	100%
Energy	0.99	1.34	0.35***	-12.9	100%	100%	100%
Financials	1.33	0.81	-0.52***	16.64	100%	100%	100%
Health Care	1.38	1.49	0.10***	-11.2	100%	100%	100%
Industrials	0.88	1.01	0.12***	-9.79	100%	100%	100%
Information Technology	0.15	0.31	0.16***	-13.1	100%	100%	100%
Materials	0.1	0.3	0.21***	-14	100%	100%	100%
Telecommunication Services	0.95	0.91	-0.04**	2.2	36%	59%	71%
Utilities	0.13	0.12	-0.01	0.51	2%	7%	14%
Pscap	0.95	0.48	-0.48***	14.35	100%	100%	100%

The table shows the de-cycled mean beta for the pre-SCAP period (from January 26, 2007 to January 23, 2009) and the post-SCAP period (from January 30, 2009 to January 28, 2011), respectively and their differences for the index sample. Last columns report the t-test for the difference and the bootstrapped simulation of the t-test (that is, the rejection rate of null hypothesis of equal average) for the canonical confidence levels (cl) of 1%, 5%, and 10%, respectively. Since reported betas are de-cycled, their value must not be interpreted using the canonical thresholds: betas lower than zero do not identify countercyclical institution.

The last three columns show the rejection rate of the t-test for the null hypothesis (thus indicating a significant mean difference) over bootstrapped samples: the results largely confirm our expectations and the evidences from the one-shot t-tests, even at multiple significance levels.

What emerges from our analyses is that the beta of the Pscap show a marked decreasing pattern, which starts from the months in which the supervisory exercise has been performed and lasts for nearly a year, while the betas of other industries do not seem to be affected by it. In other word our results seem to bring to light a reduction in systemic risk of the banking industry behind the unexpected corner solution.

6. Concluding Remarks

The 2008 financial crisis forced authorities to design a new supervisory approach, shifting their stance towards a combined micro and macro prudential procedure, which hallmark resides in the full disclosure of every part of the process, from the methodology to the results. As it is proved that financial markets are strategic environments featured with herding and cascading behaviors (Scharfstein and Stein, 1990; Hirshleifer and Hong Teoh, 2003), it becomes crucial for policy makers to understand how their choices affect markets reaction. Since Morris and Shin (2002) have started the debate about the social value of the monetary authorities' disclosure, the stabilizing ability of public information has been strongly called into question. It, hence, becomes important to test how the enhanced disclosure is able to affect markets risk perception, in order to verify whether the new supervisory approach is in line with the goal of promoting stability and enhancing systemic soundness. The model proposed in this paper yields that, after the implementation of the SCAP, agents revised downwards both their systematic and systemic risk assessments. This behavior does not align with either of the two lines proposed in the literature: the separating equilibrium proposal (e.g. Barlevy and Alvarez, 2014; Nier, 2005) and the claim that wants disclosure to increase market instability (Goldstein and Leitner, 2015; Cordella and Yeyati, 1998). Instead it seems that this approach is able to restore public confidence even in banks most severely hit by a crisis. Such outcome can be due to the structure of the test and to the FEDs assurance that all the banks found under the regulatory requirement would be provided with the capital needed to meet the threshold (as proposed by Spargoli, 2013). This was read by agents as a fresh start of the financial system, given that under capitalized banks were offered the possibility to regain an acceptable degree of soundness through a guaranteed capital injection. From these findings derive important policy implications, as it seems that the new supervisory approach, with the choice of fully disclose the results, can generate a sharp rise in investors' confidence and make them revise downwards both systematic and systemic risk assessments of banks, creating a useful paradigm to apply when dealing with market crashes.

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Notes

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[2] We tried to capture changes in riskiness by using easier models, such as linear regression (as proposed by Neretina et al., 2014), recursive least squares (RLS), and rolling regressions (RR) but they suffered different pitfalls: only the RR revealed a pattern similar to the one yielded by our state-space model; however, its specification bears identification issues that do not allow us to evaluate the net effect of the new information on betas trend.

[3] We have also employed some KF variations, such as the Smoother algorithm but we provide only the KFs results as the one of the other algorithm are qualitatively similar. Moreover, such estimates are available on request from the authors.

[4] We use the 1m T-bill as risk free rate.

[5] Four zero-vectors are needed as the variable used to model the business cycle (and mainly its influence on betas) do not have to influence directly the asset returns.

[6] Usually, time varying parameters are modelled as autoregressive random walk process, as we do for the last four betas of the state sequence. As for the FF factors, we estimate their parameters modifying the general form in order to control for the business cycle.

[7] As robustness check, we proxied the business cycle with other financial variables (M1, M2, their variations and their logarithms) as well as a real variable (the unemployment insurance weekly claims). The results are qualitatively similar, and available upon request.

8 As a consequence, the state equation for a generic beta in the t-th period is: $\beta t+1 = \beta t + \beta tcycle$ □ $3mTbrt + \eta t$ (cfr. footnote 6).

[9] Preliminary estimates of our model revealed that our error terms do not follow Normal distribution, in confirmation.

[10] The beta with the cycle apex measures the impact of the business cycle, proxied by the 3m T-bill rate, over the estimated market betas.

[11] For expositional ease, the purpose of such sample will be thoroughly discussed in the results paragraph.

[12] The Capital Assistance Program and Its Role in the Financial Stability Plan - Treasury White Paper (February, 25, 2009) https://www.treasury.gov/press-center/press-releases/Documents/tg40_capwhitepaper.pdf

Sommario

Da quando gli stress tests sono diventati i principali strumenti utilizzati dalle autorità di vigilanza, il dibattito circa la loro effettiva efficacia si è infiammato. Il nostro lavoro mira a fornire un framework che, attraverso una stima dinamica dei beta, permetta di osservare l'impatto di nuova informazione sulla stabilità del sistema bancario. I nostri risultati confermano un'ipotesi contraria rispetto la letteratura, trovando che quasi tutti i beta di mercato delle banche decrescono, grazie ad uno shock di trasparenza che contribuisce ad un calo generale del rischio sistemico

Abstract

Since macro-prudential stress tests have become the main instruments of the supervisory authorities' toolkit, the debate on the effect of their results disclosure inflamed. Our work aims at providing a framework that, via a dynamic estimation of the betas, allows to observe the impact of the new information flow on the stability of the banking system. What we find is that, contrary to literature wisdom, almost all banks betas decrease, as the transparency shock contributes to an overall systemic risk drop.

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