Did the Basel Process of Capital Regulation Enhance the Resiliency of European Banks?

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Abstract

This paper analyses the evolution of the safety and soundness of the European banking sector during the various stages of the Basel process of capital regulation. In the first part we document the evolution of various measures of systemic risk as the Basel process unfolds. Most strikingly, we find that the exposure to systemic risk as measured by SRISK has been steeply rising for the highest quintile, moderately rising for the second quintile and remaining roughly stationary for the remaining three quintiles of listed European banks. This observation suggests that the Basel process has succeeded in containing systemic risk for the majority of European banks but not for the largest and most risky institutions. In the second part we analyze the drivers of systemic risk. We find compelling evidence that the increase in exposure to systemic risk (SRISK) is intimately tied to the implementation of internal models for determining credit risk as well as market risk. Based on this evidence, the sub-prime crisis found especially the largest and more systemic banks ill-prepared and lacking resiliency. This condition has even aggravated during the European sovereign crisis. Banking Union has not (yet) brought about a significant increase in the safety and soundness of the European banking system. Finally, low interest rates considerably affect the contribution to systemic risk for the safer banks.

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1 Introduction

This paper has two main contributions: it is the first paper that traces the long-run evolution of various systemic as well as individual risk measures of banks and financial institutions over the whole period of operation of the Basel process of capital regulation across the full cross-section of institutions. The second contribution attempts to identify the drivers of the underlying economic mechanisms. How can the evolution of the various risk trajectories be explained? And in particular, how, can the substantial cross-sectional heterogeneity be explained?

These issues are of crucial importance for evaluating and reforming the Basel process, since right from the start in 1988 it has always been the intention of the Basel Committee to increase the **safety and soundness** of banks and the global banking system while at the same time maintaining a **level playing field** in an increasingly globalized banking industry (Basel Committee of Banking Supervision, 1988).[1] The Basel process has been a process of continued reform of the original minimum capital standard that did affect both the definition of capital and the risk weights of different asset categories. Most notably, the market risk amendment of 1996 and the reform package Basel II successively introduced choices between statutory risk weights or risk weights based on institutions' own calculations with the help of internal models. The experience of the Great Financial Crisis certainly suggests that the original goals might not have been reached and immediate regulatory reform was required after the Lehman insolvency, which triggered a new phase of the process now commonly referred to as Basel III. Our analysis provides insights into which aspects of regulatory reform require particular attention and scrutiny.

If the intentions of the Basel process of capital regulation had been achieved, one might have expected a general decline in measures of individual as well as systemic risk over the past 30 years, reflecting an increase in bank resiliency. However, we find differently. By tracing SRISK, a capital shortfall measure of systemic risk developed by Brownlees and Engle (2017), we observe a dramatic increase. This increase is mainly driven by the highest quintile across the distribution of SRISK, while the lowest three quintiles are increasing only weakly. But also for other measures for systemic risk such as the contribution measure of Delta CoVaR, developed by Adrian and Brunnermeier (2016) or other exposure measures like marginal expected shortfall do not show signs of a long-run reduction in systemic risk.

But also focusing on individual banking risk we cannot find a general long-run increase in bank resiliency. A cross-sectional analysis of the z-score establishes that individual bank failure risk did actually increase for the two largest quintiles until 2010. A slight recovery can be observed for the highest quintile after 2010 up to a level of resilience in the early 1990s while the second quintile remains flat after 2010 and well below the average 1990s score. An increase in resiliency can be observed, however, for the smaller three quintiles especially after 2005.

So based on simple descriptive analyses both, measures of individual bank risk as well as measures of systemic risk do not readily support the view that banking regulation in the long-run has increased the stability and soundness of the banking system at large. One might argue, for example,

[1] In its 1988 Report the Basel Committee on Banking Supervision explicitly states: "Two fundamental objectives lie at the heart of the Committee's work on regulatory convergence. These are, firstly, that the new framework should serve to strengthen the soundness and stability of the international banking system; and secondly that the framework should be in [sic!] fair and have a high degree of consistency in its application to banks in different countries with a view to diminishing an existing source of competitive inequality among international banks." (BIS, 1988)

that general economic risk factors have increased tremendously in intensity and, thus, resiliency would have been much less in the absence of any Basel regulation. Hence, a structural approach is needed to control for the quantitative contribution of economic risk factors and to identify the various drivers of bank risk, both for systematic as well as individual bank risk.

Our structural analysis builds on unconditional quantile regressions, both for our systemic risk measures as well as the idiosyncratic bank risk measures, in order to take into account the cross-distributional heterogeneity. Since the construction of SRISK builds on market values, we consider all the standard drivers of bank stock prices as controls. In addition we control for market stress, macroeconomic conditions and monetary policy as well as policy variables.

We observe that the implementation of market as well as credit risk models along Basel II regulation have a strong non-linear impact on individual bank systemic risk exposures as measured by SRISK. Market risk models tend to reduce systemic risk exposures for the lower risk quartiles of banks but, paradoxically increase systemic risk exposures at the upper quartile. Also internal risk models for credit risk tend to affects banks asymmetrically. Especially the choice of the advanced or the mixed approach to internal models largely contributes to systemic risk across all risk classes, while the standard and the foundation approach tend to moderate systemic risk exposures. Overall the introduction of self-regulatory options to calculate risk based capital on credit exposures tends to be the largest driver of systemic risk exposure during and after the crisis.

To dig even deeper, we study the effect of credit risk internal models with bank-level implementation data, and we observe a strong aggravating impact on SRISK from the implementation of advanced internal models. We also perform counter-factual exercises with behavioral parameters of the respective pre-implementation periods we simulate alternative trajectories of the systemic risk measures. Also these exercises establish that the dramatic increase in the exposure risk cannot be explained by pre-Basel II bank business models. It is rather the change of business models induced by Basel II that has become a major contributing factor of systemic exposure risk. The results is particularly robust in a difference-in-differences approach carried out on the sample of banks implementing advanced IRBA models after Basel II, versus a sample of control banks matched by propensity score matching.

There are some restrictions that limit the scope of our analysis. First by limiting our analysis to stock banks, implicitly we are only considering relatively large banks. We are not considering smaller savings banks, regional banks or cooperative banks. Second, our analysis is limited to European banks, for which we have relatively good data access also concerning the implementation dates of internal risk-based models. Another reason not to consider US-banks is that the U.S. did not widely implement Basel II.

The paper will proceed as follow: Section 2 briefly describes the Basel process. Section 3 introduces the data and methodology. Section 4 presents the main descriptive results for the systemic as well as individual bank risk measures. The structural analysis is provided in section 5. Further support for causality is presented in section 6. A potential policy role of market based risk measures is discussed in section 7. Section 8 relates our analysis to the literature before section 9 concludes.

2 The Basel Process of Capital Regulation

The Basel process of capital regulation was triggered in late 1974. The first meeting of Basel Committee on Banking Regulations and Supervisory Practices took place in February 1975. After a long period of consultations[2], the first Basel Capital Accord (Basel I) was approved by the G10 governors in December 1987 and publicly announced in July 1988. The Accord was formally implemented in December 1992.

The Accord had already been amended in 1991, to reform the treatment of loan loss reserves, and later repeatedly in 1995 and 1996. The most important amendment was the introduction of internal models under supervisory review as an alternative to statutory rules in January 1996 as part of the market risk amendment (Basel Committee of Banking Supervision, 1996). This amendment essentially provided a choice between a self-regulatory regime under supervisory review and statutory regulation. It provided incentives to improve in-house risk management models, which were highly deficient in the 1990s even in multinational banks (see Wuffli, 1995). However, the amendment also implicitly provided incentives to employ internal models as an instrument to reduce regulatory burdens and capital charges, and, hence, to reduce resiliency (see Hellwig, 1995).

Proposals for a new capital accord were triggered by the initiation of a consultation process on a Revised Capital Framework in June 1999. This became the basis of the three-pillar framework of Basel II, which formally culminated in June 2006 in the agreement on Basel II: "International convergence of capital measurement and capital standards: a revised framework for comprehensive supervision".

Basel II was adopted in most countries with the notable exception of the U.S., one of its strongest original supporters. However, the impact of its implementation could not be properly assessed[3] since already in 2007 the subprime crises developed into a worldwide crisis and depression. Hence, already in September 2008, the Basel Committee was forced to reconsider its regulatory framework with its guidelines on Principles for Sound Liquidity Risk Management and Supervision triggering the discussion on reforming Basel II, a process now commonly referred to as Basel III.

In November 2017 Basel III was finally concluded after long negotiations. A major stumbling block of the Basel III negotiations was the role of internal models. While the U.S. initially insisted to completely phase out internal credit risk models, the large European countries and especially Germany and France insisted on maintaining them while agreeing on curbing their effectiveness. The final agreement reduces the impact of internal models by a so-called output floor, that limits the amount of reduction of risk weights with internal models to 72.5% relative to the standard approach. This prolonged process of negotiations together with the results of our analysis reflect the fact that capital regulation is largely political and not primarily driven by prudential concerns and arguments.

[2]See Goodhart (2011) for details on the early years of the Basel Committee.

[3]Given the length of the consultancy process for Basel II, it is quite likely that the process did affect bank business models already well before the official implementation. Moreover, the self-regulatory pillar allowing internal models was available to officially and fully compliantly drive bank business models since 1996.

3 Data

In order to assess the implementation of the Basel principles, we conduct an empirical investigation on a sample of European financial institutions from 1987 to 2016. The sample includes the listed institutions covered by Compustat Global and classified as banks (4010), diversified institutions (4020), insurance companies (4030), and real estates companies (4040). The sample also includes institutions that exited or entered during that period. For our analysis we will consider institutions only with at least 10 years of balance sheet data. In this paper we will largely focus on banks and diversified institutions, but occasionally resort to the other institutions for identification issues. Overall we estimate systemic risk, as well as individual banking risk, for about 400 institutions from the Euro-area, Switzerland, and the United Kingdom.

Compustat Global provides us with both daily market prices and capitalization, and quarterly or annual book data, such as book values of equity, assets, debt and ROA. We use the MSCI Europe index as the broad market return (Datastream data), and the yield on German federal bonds (Bundesbank data) as the risk free rate. Moreover, we use the market stress indicator CISS from Hollo, Kremer and Lo Duca (2012). SNL provides bank-level quarterly information on the implementation of standardized versus internal models for credit risk from 2006, that we merge with the approval dates of internal models from the Bundesbank and from the Österreichische Nationalbank.

4 Measures of Bank Resiliency

The resiliency of banks can be measured both on the level of an individual bank as well as on a systemic level. In a market economy the latter are of major relevance for supervisors, since a major raison d'etre for prudential regulation and supervision is the prevention of systemic spill-overs from individual bank failures. Individual insolvencies of banking institutions, on the other hand, are not a primary reason for regulatory intervention in a market economy, where the selection of successful business models as well as the exit of unsuccessful models is delegated to market forces on purpose.

We therefore estimate several measures of systemic and individual risks. We estimate a bank's exposure to systemic risk according to the SRISK proposed by Brownlees and Engle (2017) and the Marginal Expected Shortfall (MES) theorized by Acharya, Pedersen, Philippon and Richardson (2017). A bank's contribution to the aggregate systemic risk is evinced by the Delta CoVaR developed by Adrian and Brunnermeier (2016). Finally, banks' individual risk is modelled by the Z-score as in Fiordelisi and Marques-Ibanez (2013).

4.1 Systemic Risk Measures

We start by presenting the trajectories of systemic risk measures before contrasting them to measures of individual banking risk. We find the strongest and most disconcerting results for the capital shortfall measure SRISK of Brownless and Engle (2017) and therefore start with it. We continue to present the somewhat different but complimentary results for another measure of exposure risk, marginal expected shortfall (MES) developed by Acharya et al. (2017), before presenting the trajectories for the contribution measure Delta CoVaR of Adrian and Brunnermeier (2016).[4] While

[4]The literature (see especially Giglio, Kelly, Pruitt, 2016) provides a multitude of alternative systemic measures such as additional shortfall measures like CATFIN (Allen, Bali, Tang, 2012).

the informational content differs across systemic risk measures they all agree in the fact that neither provides prima facie evidence in support of an increase in bank resiliency.

4.1.1 SRISK

SRISK is a systemic risk measure developed by Brownlees and Engle (2017) as an estimate of the expected capital shortfall after a serious macro shock. Specifically, it calculates the amount of capital that needs to be raised by each bank to face the extreme markets conditions for such an event[5] As such SRISK is a hybrid measure since it combines market information with book values. It considers the combined effect of the sensitivity of the bank returns to aggregate shocks, leverage and market capitalization of the bank, and the weakness of the whole financial system. A bank is considered systemically risky if it is likely to face a sizable capital shortfall in situations when the financial sector is weak.

We report two aggregations of the bank-level SRISK: i) in the first version we aggregate over shortfalls and surpluses of individual banks (Figure 1), and ii) in the second version we only aggregate positive shortfalls (Figure 2). While the first version does implicitly allow for inter-industry netting of bank capital, the second version measures the total amount of re-capitalization needed for a given capitalization standard. Thus, the net measure is a measure of the shortfall from a societal level after potential redistribution of bank capital, while the latter measure is an indicator of overall industry stress.

Both measures exhibit an increasing trend reflecting a steady decline in resilience. Both SRISK measures are quite low around the dot-com bubble, which may just be a reflection of the bubble per se.[6] The measure shoots up when the bubble bursts, but remains elevated prior to the subprime crisis. During the Great Recession it shoots up again after the Lehman failure, but subsequently remains at almost identically high levels during the European sovereign crisis. On the positive side though, the Basel III measures seem to be effective in preventing a further rise in SRISK, albeit at a rather high level well above pre-crisis levels.

By visual inspection of the first net-exposure measure of SRISK three major level changes in aggregate SRISK catch the eye: i) the early stage from 1988-2001, ii) the period from 2002-2008 and the iii) sovereign crisis stage from 2009 onwards. When aggregating only positive shortfalls across institutions, a steady increase of exposure to systemic risk is observed until 2008 from which on it remains constant at almost 2008 levels.

On first sight, this evidence on the exposure to systemic risk seems to contradict the original intentions of the Basel accord of the increasing safety and soundness in banking. Of course, such a judgement ultimately requires to control for the evolution of bank risk, which we will do in the structural analysis. Before we do so in section 6, it may however be quite informative, to have a look at the whole distribution of banks rather than only focusing on the mean. Will the distributional perspective allow us to locate some of the sources of the build-up in risk exposure or has it evolved uniformly across the whole distribution of banks?

[5] The precise technical implementation of SRISK for our analysis is described in the Appendix.

[6] Since SRISK is a market-based risk measure it underestimates true exposure to systemic risk in periods of overpricing (bubbles) and it overestimates true exposure to systemic risk in periods of underpricing. In this sense SRISK is not a useful early warning indicator.

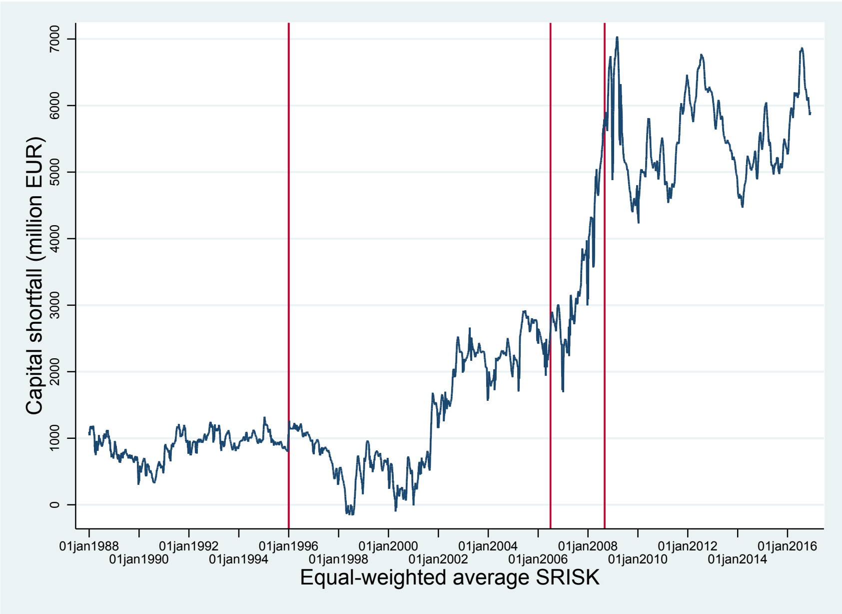

Figure 1: Evolution of exposure to systemic risk - equal weigthed average SRISK. The Figure reports the evolution of the daily average estimated SRISK in Equation 13. We report a central moving average of 20 days. We consider both positive and negative values of SRISK, respectively as shortfall and surplus of capital. The SRISK is estimated by MLE using a GJR-DCC Garch model. We use a capital ratio k=8%.

Figure 2: Evolution of exposure to systemic risk - average positive SRISK. The Figure reports the evolution of the daily average estimated SRISK (Equation 13) in case of capital need (positive SRISK). We report a central moving average of 20 days, and we consider only positive values of SRISK, representing the capital shortfall in the system. The SRISK is estimated by MLE using a GJR-DCC Garch model. We use a capital ratio k=8%.

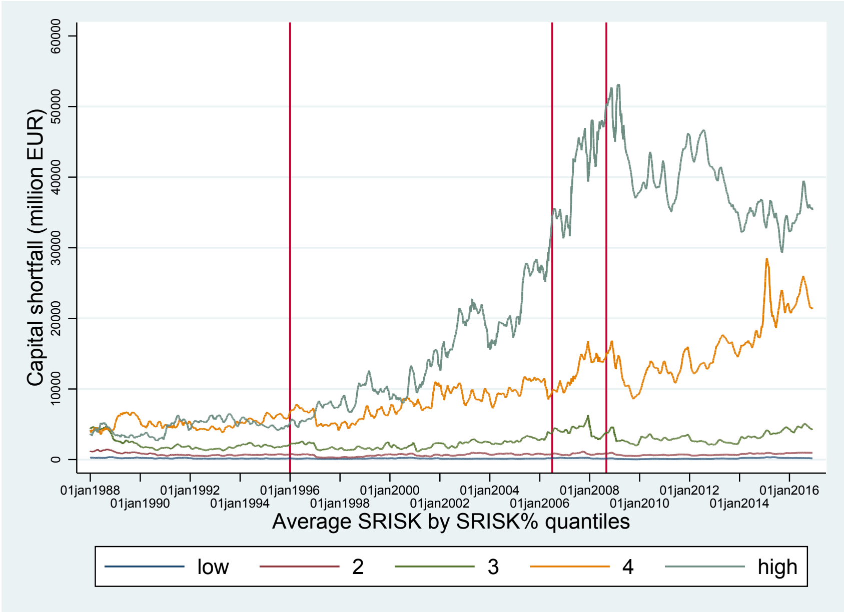

Figure 3: Quantile effects and non-linearities. The first frame reports the evolution of the daily average estimated SRISK (Equation 13), distinguishing five equal-size quintiles of contribution to capital shortfall (SRISK%), as in Equation 14. The top quintile (gr5) corresponds to the group of banks with the highest level of positive SRISK, while the bottom quintile (gr1) corresponds to the group of banks with the lowest level of capital shortfall. We report a central moving average of 50 days, and we average both positive and negative values of SRISK.

Accordingly, we analyze the quintiles of the SRISK-distribution. It turns out that it is essentially the upper two quintiles that cause most of the increase in SRISK, while the risk exposure for the majority of banks has increased only slightly until 2016 (Figure 3). In any case the trajectories do not seem to reflect a long term increase in resiliency. It is interesting to note that the introduction of internal market risk models in 1996 seems to have exerted a short-lived but discernible moderating effect on the SRISK-trajectories across all quintiles (Figure 3).

4.1.2 MES

While SRISK is a hybrid risk measure that combines accounting information with market information, it is also illustrative to consult risk measures that only exploit market information. As such present descriptive evidence for the exposure measure MES as well as the contribution measure Delta Covar in the next section.

MES has been developed by Acharya et al. (2017) and corresponds to the daily loss that a bank faces on the bad outcomes of the sector returns. Its trajectory (Figure 4) unsurprisingly looks quite different as compared to SRISK; it is more volatile and trending upwards only slowly across the three decades. While it peaks as well during the Great Financial Crisis, this measure seems to return more quickly to pre-cisis level even though it picks up some peeks during the European Sovereign Crisis.

Overall the increase in MES is less drastic than SRISK but like SRISK there is no indication of

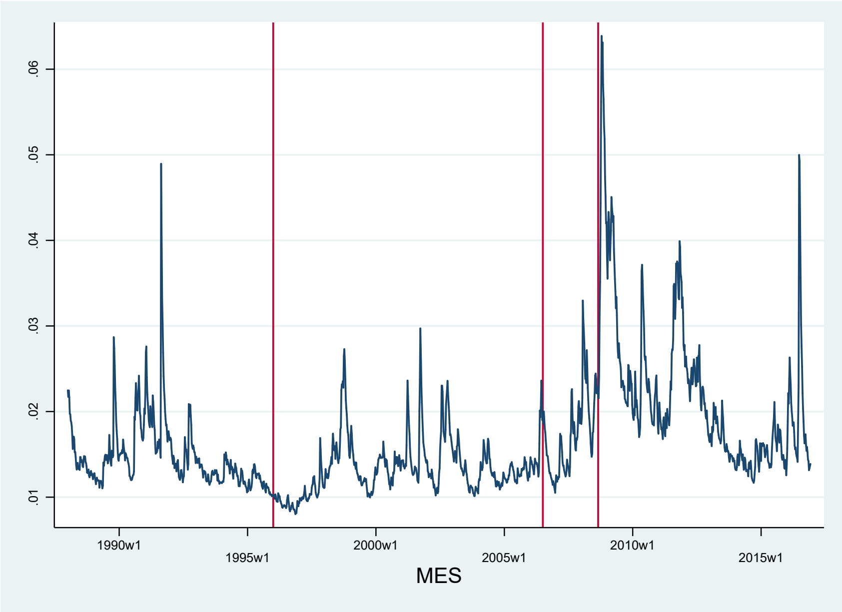

Figure 4: Evolution of exposure to systemic risk - marginal expected shortfall (MES). The Figure reports the evolution of the daily average estimated SRISK (Equation 13) in case of capital need (positive SRISK). We report a central moving average of 20 days, and we consider only positive values of SRISK, representing the capital shortfall in the system. The SRISK is estimated by MLE using a GJR-DCC Garch model. We use a capital ratio k=8%.

an increase in bank resilience. In contrast to SRISK we find much less cross-sectional heterogeneity in MES (see 13 in the Appendix).

4.1.3 Delta CoVaR

Delta CoVaR developed by Adrian and Brunnermeier (2016) also is a purely market based systemic risk measure, but, in contrast to SRISK and MES, it measures the contribution of a financial institution to systemic risk. Delta CoVaR is the market VaR conditional on a bank being in distress. Hence, it measures the contagion deriving from a bank being in distress to the whole banking system.

Delta CoVaR first peaks in the late 1980's at the end of the S&L crisis. After the Basel accord of 1988 the Delta CoVaR measure is in decline until 1996, from which on it remains heightened until about 2005 (Figure 5). This period roughly corresponds with the period after the introduction of the market risk amendment of Basel I until the end of the consultancy process of Basel II. This period also covers the dot-com bubble, which did not affect contagion risk of European banks. The next huge increase in Delta CoVaR coincides with the European sovereign crisis in 2009-10.

The trajectories of Delta CoVaR resemble closely those of MES but differ significantly from SRISK. The subprime crisis does not figure prominently according to the Delta CoVaR measure. There is a single peak around the Lehman failure in September 2008, but Delta CoVaR remains below pre-crisis levels. To the effect that the subprime crisis has been characterized by a drying-up of liquidity, it appears remarkable that contagion risk has not shot up dramatically during the 2007-8 period prior to the Lehman insolvency.

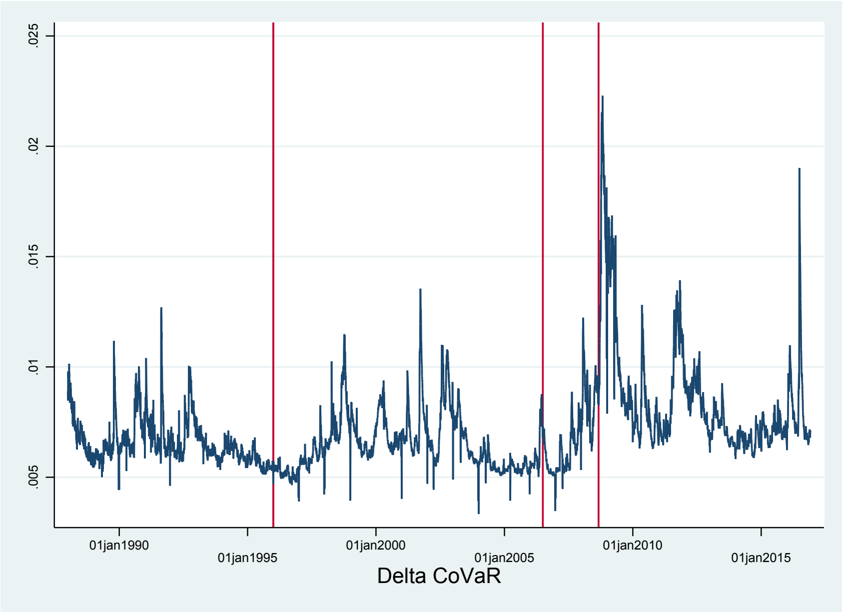

Figure 5: Evolution of contribution to systemic risk - Delta CoVaR. The Figure reports the evolution of the daily average estimated Delta CoVaR in Equation 8, estimated with quantile regressions.

By way of summarizing, the trajectories of the systemic risk measure under consideration agree at least to the extent that a visible increase in resiliency cannot be observed during the 30 years of operation of the Basel process.

4.2 Individual Bank Risk Measures

How about individual bank risk rather than systemic concerns? Did the Basel process succeed to significantly enhance the resiliency of individual banks? In order to address these questions we analyze the trajectories of individual bank measures of default. Distance of default is widely proxied in the banking literature by the z-score (Boyd and Runkle, 1993, Fiordelisi and Marques-Ibanez, 2013). It measures the distance to becoming insolvent, as number of standard deviations away from the bank's ROA.

Again it is illustrative to take a cross-sectional perspective (Fig. 6). Accordingly, we sort banks according to their SRISK scores and trace their z-score trajectories. It becomes readily apparent, that resiliency as measured by distance from default has been markedly increasing for the lowest two quintiles of the SRISK-distribution, while it has been decreasing for the highest risk groups. [7]

Across almost three decades individual bank risk has been significantly reduced for the two quintiles of banks that pose the smallest systemic concerns according to their SRISK-scores. For the upper three SRISK-quintiles no quantitatively important long-run improvement of the z-score can

[7] See also Figure 15 in the Appendix with adjustable scales.

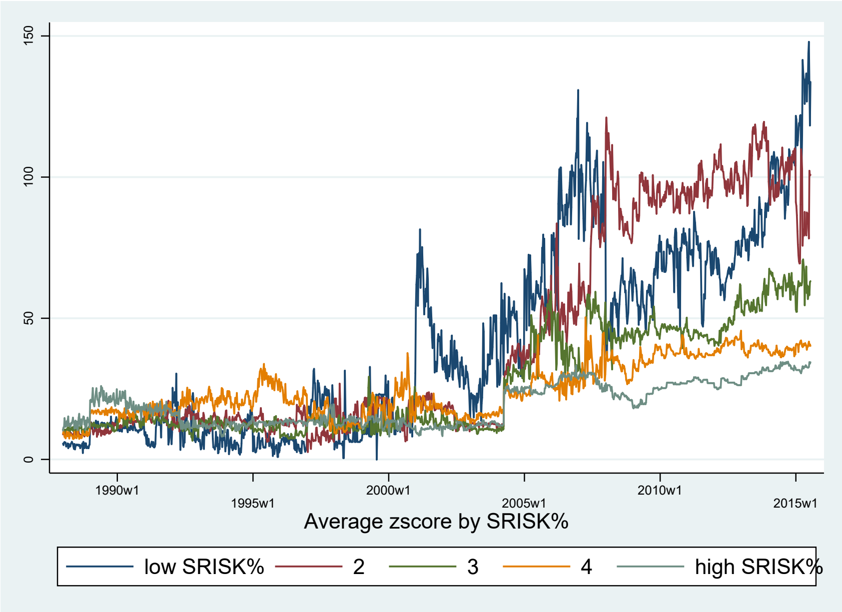

Figure 6: Evolution of idiosyncratic bank risk according to risk group. The trajectories report the evolution of the z-score according to risk groups sorted by SRISK%.

be observed. To the contrary, fragility as measured by the z-score has even increased for precisely those banks that also pose the highest systemic concerns.

Summarizing the evidence on the various risk measures we observe quite heterogeneous and unequal developments across our sample of banks. While it seems that some banks have become safer, the most systemic banks have not. The evidence presented so far does not speak in favor of a general increase in safety and soundness across the whole banking system despite regulatory efforts and the reforms during the Basel process of capital regulation. The evidence, however, does not necessarily speak against the success of regulatory reform per se, since the decrease in resiliency might just reflect an increasingly more risky environment of the global banking business. For such an assessment a deeper multivariate structural analysis is required that controls for the observable risk factors.

5 Sources of Bank Risk

Let us now turn to the economic and political drivers of the observed risk measures. To what extent can these observations be related to the realization of standard risk factors and to what extent are they affected, moderated or amplified, by regulatory intervention? We will analyze systemic risk exposure first and then individual banking risk. We will apply quantile regressions to allow for distributional heterogeneity as observed above in the descriptive analyses of section 4.

5.1 Drivers of Capital Shortfall

Capital shortfall is a measure of exposure to systemic risk. We concentrate on SRISK, which is a hybrid measure that relates market values to book values. Accordingly, all known drivers of bank asset prices will also affect SRISK.

On the level of policy variables we have detailed bank-level information about internal credit risk models (IRBA). In particular, we know when banks were given permission to implement which type of model. With the introduction of Basel II, banks were allowed to use in-house internal models to quantify risks of their loan portfolios instead of the standardized approach where the risk weights are assigned by coarse categories by the regulator. They have two options on how to implement IRBA, subject to authority approval: a foundation approach and an advanced approach. Under the former, banks are allowed to build their own models estimating the probability of default of individual clients or portfolios of loans. Under an advanced approach, banks can also estimate internally exposure-at-default and loss-given-default in order to quantify the risk-weighted assets.

We therefore regress weekly SRISK on a bank-level categorical variable, $IRBA_{it}$, equal to 1 for standardized models as Basel II regulation, 2 for the implementation of foundation internal models, 3 for advanced or mixed IRBA models, and 0 before the introduction of Basel II regulations. To account for the dynamic patterns in our date, we regress a dynamic panel data model of SRISK on market- and bank-characteristics:

$$\begin{aligned} SRISK_{it} &= \alpha + \gamma_0 L.SRISK_i + \sum_k \gamma_k L.Z_{kit} + \sum_q \gamma_q L.X_{qt} \\ &+ \lambda_1 BIAmend + \sum_p \lambda_p IRBA_{pit} + \mu_i + \tau + \varepsilon_{it} \end{aligned} \tag{1}$$

We control for market-characteristics (X_{qt}) that would proxy for market investment opportunities (European market return, country interest rates, market stress indicator CISS), and bank-characteristics (Z_{kit}) as Beta, market capitalization, intrinsic distance to default Z-score, and market over- or undervaluation of the bank (market-to-book ratio). We regress the panel model with year effects and with fixed effects μ_i for either bank or country. As SRISK is a market variable of risk, we address the main factors in the asset pricing literature, market return, size and market-to-book, as drivers of market prices that could introduce endogeneity in our model. Moreover, the introduction of country interest rates allow us in order to control for monetary policy and growth opportunities.

Since we observe important nonlinearities in SRISK, we use quantile regressions to address potentially differential effects of our covariates across the three main quantiles (q25, q50 and q75) of the distribution of SRISK. We use an unconditional quantile approach as Firpo, Fortin and Lemieux (2009), where we marginalize the quantile coefficients using the recentered influence function. The interpretation of the estimated coefficients therefore corresponds to the usual interpretation as the marginal effect on the unconditional quantile of SRISK of a location shift in the distribution of the covariates, ceteris paribus.

We investigate this self-regulatory tool, looking now at credit risk internal models. One of the pillars of Basel II is the option to widen the scope for internal models also to cover credit risks. While at this stage we do not have sufficiently many (micro) data on the implementation or approval of internal models for market risk, we obtained this micro information about approval and/or adoption of internal credit rating models for a subsample of 100 European banks.[8]

Accordingly, we investigate the relation between SRISK and Basel regulation on the basis of the available bank-level data on the implementation of internal credit risk models. We recall that the variable IRBA takes the value 0 before 2006, the value 1 for the standardized approach, 2 for Foundation-IRBA, 3 for advanced and mixed IRBA for credit risk.

Table 1 reports the results of weekly quantiles regressions of SRISK on our IRBA variables, and a set of control variables for both market (European market return, LT interest rates, CISS) and bank (Beta, z-score, market capitalization, Market-to-Book ratio). Banks that implement internal models are larger in size, therefore we include the IRBA dummies with and without interaction with the market value of the bank. We also include a time dummy to identify the introduction of internal models for market risk in 1996.

Our strongest results obtain when allowing for country and year fixed effects. In these regressions implicitly we do allow for supervisory heterogeneity across jurisdictions as well as for other country-specific differences such as regional economic conditions.

The standard controls as well as the drivers of bank stock prices exert the expected results. Systematic risk, as measured by Beta, and the CISS stress measure significantly contribute to systemic risk exposure, while distance to default reduce it. Also market mis-pricing in form of low book-to-market valuations significantly contributes to capital short-fall.[9]

We find that internal models do exert a significant and positive effect on exposure to systemic risk. Especially the mixed and advanced approaches contribute strongly to increasing systemic exposure of banks throughout the distribution, while the standardized approach tends to be risk reducing in the medium quartile but risk enhancing in the lower and the upper quartile.

The interaction terms with size suggest that larger firms employ better models. Accordingly, the SRISK exposure of mixed or advanced models is moderated by firm size except for the highest quartile. The direct effect, however, dominates the interaction effect.Accordingly, the choice of using sophisticated internal models to estimate credit risk contributes to the systemic risk exposure especially for the largest banks.

Interestingly, the market risk dummy affects capital shortfall differentially. While models for market risk tend to reduce systemic risk exposure for the lower quartiles they exert a strong risk enhancing effect in the upper quartile. This result is in line with visual inspection of the SRISK trajectories in Figure 3. It suggests that the market risk amendment had an ambiguous effect on the resiliency of banks; while it contributed to the resiliency of the less risky banks, paradoxically it contributed to an increase in capital shortfall for the most risky banks.

[8] We are in the process of extending this dataset to all banks. The SNL dataset covers fewer European banks than Compustat, and from 2005. Therefore the sample needs to be complemented by search for hand-collected implementation dates of market risk models before 2005, and for credit risk models for the institutions not reported in SNL. We gratefully acknowledge the support of the Bundesbank and the Austrian National Bank in providing the data for all banks in their respective countries. The current subsample is already large enough to allow for meaningful analyses. Behn and Haselmann (2016) analyse an even smaller subsample of German banks.

[9] Accordingly, price bubbles in bank stocks are stabilizing according to our SRISK measure. This may be seen as a limiting feature in using SRISK for predictive purposes. Nevertheless the measure is forceful in backward looking ex-post evaluations across longer periods.

The country fixed effects are measured relative to Austria. Our estimates suggest that Belgium and France tend to tolerate larger capital shortfalls throughout the distribution, while supervision in virtually all other countries considered is stricter especially in the upper quartile.

These results are fairly robust with respect to different models, different measures of systematic risk or contribution to systemic risk not reported here.[10] This evidence stands in stark contrast to the original goals of the Basel Committee in strengthening the safety and soundness of the whole banking system.

In sum, we find no evidence that the introduction of internal models introduced in 2006 did succeed to increase bank resiliency. The discretion given to the regulated banks apparently, while in compliance with statutory regulation, did not stop banks from engaging in (sophisticated) risk taking activities. The next section aims at showing the robustness of these results in a counterfactual analysis.

So far our analysis concurs with and complements the findings of Behn, Haselmann and Vig (2016), which was conducted only for German banks. We take a European perspective and relate the impact of credit risk models to the impact of market risk models. It turns out that market risk models had a small but stabilizing effect in contrast to credit risk models. Taking a distributional approach we find that the risk enhancing effect of internal models for credit risk are increasing in the systemical importance of banks; in larger and more systemic banks internal models contribute more strongly to an increase in SRISK of European banks and across risk classes. Moreover, we find evidence for heterogeneity in the supervisory approach across European countries. Based on our results the concerns raised about Basel II by Danielson et al. (2001) seem more than justified. By neglecting the endogeneity of systemic risk, Basel II regulation did not succeed to reduce systemic risk ironically precisely in those sectors that turned out to become the most vulnerable ones.

The implementation of Basel II in July 2006 has contributed to moderate the build-up of systemic risk. However, the moderating effect is less striking for precisely the major contributors to systemic risk. In this regard, the speculation of Hakenes and Schnabel (2011) is not supported by the data. Based on theoretical considerations Hakenes and Schnabel argue that the IRB-approach of Basel II induced smaller and medium-sized banks to take larger risks in order to compete effectively with larger banks employing the IRB-approach. We find that their basic assumption that IRB contributes positively to larger banks is not supported by the data.[11]

In summary, the intended consequences of the Basel regulation were achieved only for the safer banks, but, ironically, they were missed out for the riskier banks. Obviously, banks' strategic incentives were not properly understood and the substitutability between capital rules and state guarantees was seriously underestimated throughout the various stages of the Basel process. Consequently, it was especially the systemically important European banks that were ill prepared to deal with the subprime crisis in 2007 and even more in the subsequent European sovereign crisis.

[10] The Appendix reports a quantile regression for Delta CoVaR in Table 6 with a similar main result: mixed and advanced IRB models contribute positively to systemic risk exposure across the whole distribution.

[11] Even if the competitive effect of Hakenes and Schnabel (2011) is relevant at all, our evidence suggests that the direct (negative) implications for banks' risk management are dominant. However, our findings about the effects of internal models suggest that the assumption of an increase in resiliency or the largest banks due to the use of risk-models is not supported by the data. In this regard, also Colliard (2015) has investigated theoretically the impact of internal models on the risk-taking behaviour of banks.

Table 1: Weekly Unconditional Quantile Regressions of SRISK (k=0.08%)

	(1) Q.25	(2) Q.50	(3) Q.75	(4) Q.25	(5) Q.50	(6) Q.75
L.SRISK	0.00849***	0.00354***	0.205***	0.00947***	0.00806***	0.193***
	(0.000152)	(0.000148)	(0.00343)	(0.000179)	(0.000178)	(0.00384)
Z-score	-1.400***	0.288***	-51.18***	-1.478***	-1.171***	-43.53***
	(0.0517)	(0.0633)	(0.698)	(0.0612)	(0.0765)	(0.814)
L.Beta	122.1***	165.0***	3,805***	117.2***	127.0***	3,956***
	(5.990)	(6.679)	(116.8)	(6.045)	(6.271)	(117.1)
LCISSw	86.94***	333.0***	5,714***	56.43**	233.4***	5,841***
	(26.78)	(27.72)	(426.5)	(26.75)	(26.89)	(422.2)
L.Market Return	539.9	-123.8	-6,371	587.6	-10.79	-6,290
	(401.6)	(410.9)	(6,166)	(399.9)	(394.5)	(6,099)
L.LT Interest Rate	3,152***	8,830***	132,174***	3,071***	7,538***	138,363***
	(145.2)	(208.7)	(3,703)	(152.7)	(221.3)	(3,939)
ln(Market Value)	-83.55***	152.1***	2,188***	-53.99***	164.8***	2,547***
	(1.477)	(1.541)	(24.79)	(2.078)	(1.862)	(32.41)
Market-to-Book	-2.843***	-3.481***	-28.27***	-2.888***	-3.216***	-30.58***
	(0.899)	(0.909)	(7.587)	(0.900)	(0.868)	(7.840)
IRBA1	10.86	-170.0***	-167.6	356.2***	-255.0***	5,465***
	(17.04)	(18.11)	(238.1)	(23.86)	(22.35)	(335.8)
IRBA2	143.5***	371.0***	-2,039***	199.5***	1,512***	-10,172***
	(18.65)	(21.16)	(271.1)	(33.30)	(40.61)	(589.2)
IRBA3	202.7***	114.8***	3,187***	902.6***	2,008***	2,626***
	(17.55)	(19.59)	(272.3)	(33.59)	(40.66)	(625.2)
lmvw_IRBA1				-53.58***	30.06***	-990.1***
				(2.772)	(2.496)	(45.67)
lmvw_IRBA2				-3.536	-161.6***	1,228***
				(4.830)	(5.732)	(87.45)
lmvw_IRBA3				-88.17***	-226.2***	-13.60
				(3.612)	(4.281)	(73.28)
Market Risk Amendment	-126.6***	-225.4***	6,733***	-140.0***	-248.6***	6,683***
	(36.72)	(37.43)	(720.9)	(35.50)	(37.45)	(709.9)
Constant	675.3***	-1,282***	-21,385***	473.8***	-1,203***	-24,807***
	(31.38)	(34.34)	(640.3)	(33.11)	(35.60)	(658.4)
coun==BEL	57.14***	107.4***	6,443***	83.90***	221.7***	6,229***
	(15.30)	(15.80)	(320.0)	(15.36)	(16.39)	(320.4)
coun==CYP	-163.3***	37.10*	-11,376***	-166.4***	-39.76*	-10,992***
	(15.00)	(21.13)	(231.1)	(15.38)	(20.94)	(230.1)
coun==DEU	-490.5***	-248.1***	-4,886***	-522.5***	-334.7***	-4,896***
	(11.83)	(13.11)	(185.1)	(12.22)	(12.67)	(187.1)
coun==ESP	-292.0***	-375.0***	-7,076***	-302.2***	-295.7***	-7,731***
	(14.33)	(16.94)	(282.3)	(14.67)	(16.85)	(286.3)
coun==FRA	78.74***	612.0***	3,647***	50.20***	455.3***	4,290***
	(10.67)	(14.31)	(217.0)	(11.18)	(14.53)	(232.4)
coun==GBR	-398.7***	-398.3***	-6,807***	-417.6***	-405.1***	-7,065***
	(13.93)	(14.23)	(235.3)	(14.00)	(14.30)	(231.8)
coun==GRC	-597.5***	-539.7***	-13,286***	-617.2***	-627.8***	-13,059***
	(17.03)	(19.36)	(277.0)	(17.48)	(19.37)	(281.2)
coun==IRL	-362.2***	-238.5***	-11,688***	-406.0***	-315.5***	-11,922***
	(17.58)	(22.43)	(325.7)	(17.51)	(20.80)	(328.9)
coun==ITA	-244.8***	-25.99*	-9,148***	-239.4***	-152.2***	-8,308***
	(12.59)	(14.66)	(225.6)	(13.27)	(14.54)	(228.3)
coun==NDL	147.4***	959.6***	-11,000***	110.8***	732.0***	-10,225***
	(11.94)	(15.65)	(205.2)	(13.62)	(19.35)	(214.1)
Year effects	yes***	yes***	yes***	yes***	yes***	yes***
Observations	58,612	58,612	58,612	58,612	58,612	58,612
R-squared	0.248	0.561	0.623	0.258	0.588	0.629

[a] This table reports the results from the .25, .50 and .75 unconditional quantile regressions of weekly SRISK (Firpo, Fortin and Lemiux, 2009). We include the bank-level IRBA dummies (categories 1 to 3) with and without interaction with the market capitalization of the bank, the internal model dummy (from January 1996). We control for firm effects (1 to 3) or country effects (4 to 6), CISS systemic stress, market capitalization, market investment opportunities proxied by the MSCI equity index and short-term interest rate proxy the country policy rates. The standard errors are clustered for banks (Parente et al. 2016).

5.2 Drivers of Individual Bank Risk

It has often been argued that pre-crisis the Basel process was focused on micro-prudential regulation targeted towards individual bank risk rather than macro-prudential concerns moving to center stage after the crisis. Given the rather diverse evolution of the trajectories of z-score across different risk classes of banks it is illuminating to analyze the policy effects on individual bank risk by means of quantile regressions as well.

As in our prior study on systemic risk our strongest results obtain for the country fixed effect model (see Table 2). And again the distance to default is reduced for banks that opt for the mixed or advanced approach in the highest risk quartile according to z-score. However, in contrast to our earlier analysis, in the lower quartiles all categories including the mixed and advanced models do exert a positive impact on individual bank resiliency.

The direct effects are moderated by the interaction terms with size. In particular, the most risky firms tend to have better models, partially reducing the negative impact of those models in the first place. Still the aggregate impact is dominated by the direct effect and remains destabilizing.

As before the market risk amendment has an ambiguous effect on individual bank resiliency; it tends to stabilize in the lower and medium quartile, but it contributes to increasing insolvency risk for the most risky banks.

The country-fixed effects imply that the Netherlands has had the strongest positive effect on the upper quartile while the France had been strongest on the medium and Netherlands again in the lower quartile. On the other side Belgium is lowest in the upper quartile, and Greece in the lower quartiles. As expected, the country specific effects on individual bank risk are generally different from the effects on systemic risk.

Interestingly, also the effect of interest rates is ambiguous across the distribution. The level of interest rates tends to be destabilizing in upper quartiles while it tend to be stabilizing in the lower quartile. This implies that a low interest rate monetary policy contributes to the resiliency of banks in the upper quartiles but reduces resiliency in the lowest quartile.

In summary our findings are rather mixed. While internal models benefit the less risky banks in our sample, in terms of resiliency they contribute to reducing the stability of the systemically important banks. Overall, the role of internal credit risk models remains ambiguous also on the level of individual banking risk. However, it is fair to say that we cannot find evidence in favor of internal credit risk models contributing to a general increase in safety and soundness of the European banking system.

6 Further Support for Causality

While we try our best to rule out the omission of important variables, we can never be really sure to control all relevant variables. For example, there could be hidden structural changes and relevant

Table 2: Weekly Unconditional Quantile Regressions of Z-Score

	(1) Q.25	(2) Q.50	(3) Q.75	(4) Q.25	(5) Q.50	(6) Q.75
L.Z-score	0.0617***	0.221***	0.667***	0.0593***	0.206***	0.635***
	(0.000952)	(0.00270)	(0.00609)	(0.00109)	(0.00283)	(0.00619)
L.Beta	-0.461***	-2.307***	-7.595***	-0.442***	-2.434***	-7.961***
	(0.125)	(0.226)	(0.387)	(0.125)	(0.224)	(0.385)
LCISSw	1.166**	-1.429	1.433	0.977*	-1.412	2.362
	(0.544)	(1.058)	(1.843)	(0.544)	(1.052)	(1.764)
L.Market Return	-5.561	-4.048	-15.45	-5.381	-4.434	-18.56
	(8.195)	(15.25)	(25.32)	(8.173)	(15.17)	(24.16)
L.LT Interest Rate	37.51***	-41.75***	-30.53***	37.24***	-55.82***	-48.71***
	(2.789)	(4.537)	(6.550)	(2.833)	(4.923)	(7.266)
ln(Market Value)	1.795***	3.338***	3.501***	2.147***	2.592***	0.903***
	(0.0319)	(0.0535)	(0.0861)	(0.0432)	(0.0703)	(0.0940)
Market-to-Book	-0.0536***	-0.0565***	-0.0137***	-0.0542***	-0.0535***	-0.00143
	(0.00702)	(0.00883)	(0.00335)	(0.00714)	(0.00862)	(0.00287)
IRBA1	0.0390	-2.179***	-13.98***	3.496***	-14.35***	-51.28***
	(0.273)	(0.578)	(1.121)	(0.529)	(0.885)	(1.419)
IRBA2	0.324	5.828***	18.72***	11.88***	11.26***	88.26***
	(0.313)	(0.632)	(1.421)	(0.615)	(1.463)	(3.026)
IRBA3	0.569**	5.740***	-4.723***	6.887***	6.186***	-34.96***
	(0.275)	(0.611)	(1.181)	(0.583)	(1.336)	(2.748)
lmvw_IRBA1				-0.457***	2.031***	6.549***
				(0.0669)	(0.106)	(0.148)
lmvw_IRBA2				-1.646***	-0.886***	-10.53***
				(0.0930)	(0.201)	(0.340)
lmvw_IRBA3				-0.725***	0.0799	4.371***
				(0.0622)	(0.141)	(0.276)
Market Risk Amendment	-1.152*	-8.503***	1.763**	-1.279**	-8.546***	1.494*
	(0.642)	(1.272)	(0.808)	(0.642)	(1.263)	(0.794)
Constant	-7.505***	-18.92***	-40.75***	-10.00***	-12.04***	-19.27***
	(0.609)	(1.193)	(1.165)	(0.657)	(1.251)	(1.173)
coun==BEL	-1.298***	2.612**	-18.39***	-1.435***	3.011***	-19.81***
	(0.308)	(1.027)	(0.766)	(0.310)	(1.018)	(0.799)
coun==CYP	-4.738***	-5.922***	5.618***	-4.615***	-6.690***	4.605***
	(0.451)	(0.662)	(0.674)	(0.453)	(0.664)	(0.683)
coun==DEU	-1.415***	5.565***	24.09***	-1.440***	5.647***	26.30***
	(0.182)	(0.352)	(0.644)	(0.184)	(0.352)	(0.634)
coun==ESP	0.450**	4.926***	39.33***	0.495***	6.012***	43.01***
	(0.182)	(0.425)	(0.916)	(0.181)	(0.429)	(0.863)
coun==FRA	0.812***	7.270***	8.534***	-0.0502	7.051***	4.705***
	(0.175)	(0.427)	(0.876)	(0.179)	(0.448)	(0.892)
coun==GBR	-3.320***	-0.0562	16.16***	-3.355***	0.605	18.32***
	(0.226)	(0.490)	(0.801)	(0.225)	(0.481)	(0.760)
coun==GRC	-28.16***	-24.89***	4.167***	-28.45***	-25.48***	3.973***
	(0.251)	(0.438)	(0.734)	(0.259)	(0.447)	(0.735)
coun==IRL	-17.90***	-19.48***	2.162***	-18.27***	-19.30***	5.509***
	(0.371)	(0.536)	(0.754)	(0.373)	(0.531)	(0.764)
coun==ITA	-1.672***	3.925***	11.42***	-1.730***	2.255***	7.484***
	(0.214)	(0.471)	(0.775)	(0.226)	(0.488)	(0.782)
coun==NDL	6.240***	8.249***	51.43***	5.954***	6.656***	50.19***
	(0.230)	(0.728)	(1.789)	(0.248)	(0.733)	(1.852)
Year effects	yes***	yes***	yes***	yes***	yes***	yes***
Observations	58,527	58,527	58,527	58,527	58,527	58,527
R-squared	0.381	0.460	0.564	0.384	0.464	0.590

[a] This table reports the results from the .25, .50 and .75 unconditional quantile regressions of weekly Z-score (Fiordelisi and Marques-Ibanez, 2013). We include the bank-level IRBA dummies (categories 1 to 3) with and without interaction with the market capitalization of the bank, the internal model dummy (from January 1996). We control for firm effects (1 to 3) or country effects (4 to 6), CISS systemic stress, market capitalization, market investment opportunities proxied by the MSCI equity index and short-term interest rate proxy the country policy rates. The standard errors are clustered for banks (Parente et al. 2016).

information may not be readily observable. For that reason we try two further approaches to check for the validity of causal interpretations. In our first approach, using a decomposition in the spirit of Oaxaca-Blinder (Blinder, 1973, Oaxaca, 1973), we separate the underlying risk factors from changes in behaviour induced by policy variables. In our second approach, we try a diff-in-diff methodology to check whether the adoption of internal models did contribute to changes in bank business models.

6.1 Changing Behaviour

In order to assess the contribution of certain elements of the Basel process to the build-up of aggregate risk exposure, we provide a simple counter-factual analysis by asking the question of how would the evolution of risk exposure have occurred in the absence of those policy measures. The difference between the realized and the predicted trajectories will then inform about changes in behaviour induced by the policy instruments. Thus we attempt to identify the effect of changes in behaviour induced by the introduction of internal models.[12]

For our analysis we concentrate on two major policy events, i) the introduction of internal market risk models in the market risk amendment of 1996 and ii) the internal credit risk models with the adoption of the Basel II framework in 2006.

Our analysis is performed in two stages: First, we apply the former weekly panel specification to estimate the parameters in two pre-Basel windows:

$$SRISK^e_{it} = \alpha + \sum_k \gamma_k L.Z_{kit} + \sum_q \gamma_q L.X_{qt} + \mu_i + \varepsilon_{it} \tag{2}$$

For estimating the parameters we distinguish two estimation periods, i) the period prior to the Market Risk Amendment (January 1996), and ii) the period prior to Basel II regulation (June 2006).

Next, in the second stage, we predict what SRISK would have been in the following periods after the policy implementation assuming constant parameters. This generates two post-event windows where we predict SRISK as:

$$\widehat{SRISK}^{(e,noMRA)}_{i\tau} = \widehat{\alpha} + \sum_k \widehat{\gamma}^{(\tau<Jan1996)}_k L.Z_{kit} + \sum_q \widehat{\gamma}^{(\tau<Jan1996)}_q L.X_{qt} \tag{3}$$

$$\widehat{SRISK}^{(e,noBII)}_{i\tau} = \widehat{\alpha} + \sum_k \widehat{\gamma}^{(Jan1996\leq\tau<Jun2006)}_k L.Z_{kit} + \sum_q \widehat{\gamma}^{(Jan1996\leq\tau<Jun2006)}_q L.X_{qt} \tag{4}$$

Comparing the observed SRISK with the predicted $\widehat{SRISK}$ helps us to reach an interpretation of the effects of Basel regulation on the banks resiliency.

Figure 7 shows the historical evolution of SRISK compared to the estimated forecasted SRISK in case of no changes in the regulatory environment. We present trajectories both for total exposure and average exposure, since the number of banks in our dataset is not constant over time. The results of the mean panel regression suggest that the internal models for market risk did indeed mildly reduce

[12]This approach follows Fuess et al. (2016).

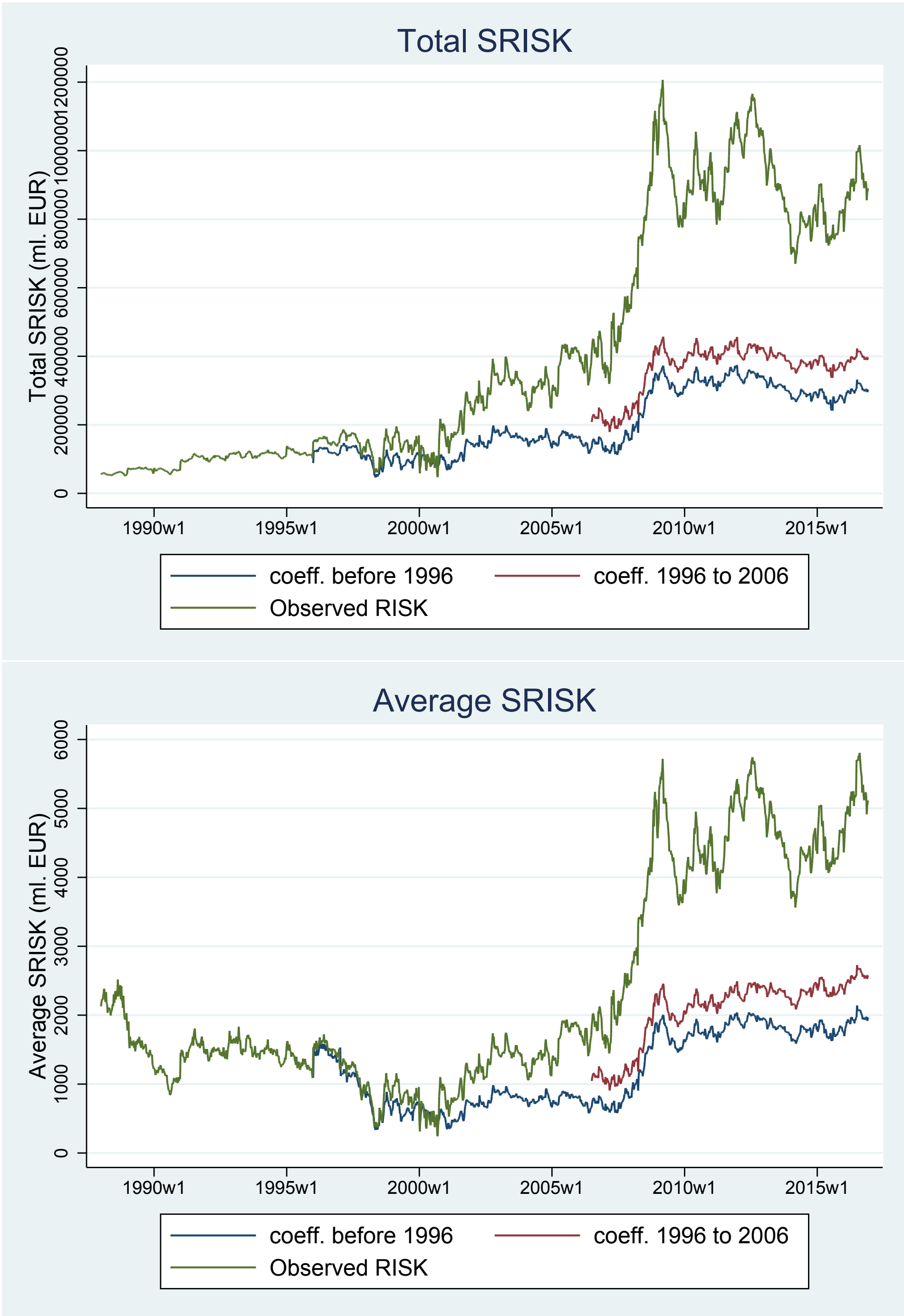

Figure 7: Evolution of historical total and average SRISK vs. counterfactual SRISK. The Figure presents the evolution of the historical average SRISK compared with the estimated forecasted SRISK in case of no Market Risk Amendment (blue line) and no Basel II accord (red line). We estimate SRISK using the dynamic two-stage model as Equation 1 in two sub-periods: i) before any internal models were available (prior to 1996) and ii) prior to the implementation of internal credit risk models (1996-2006).

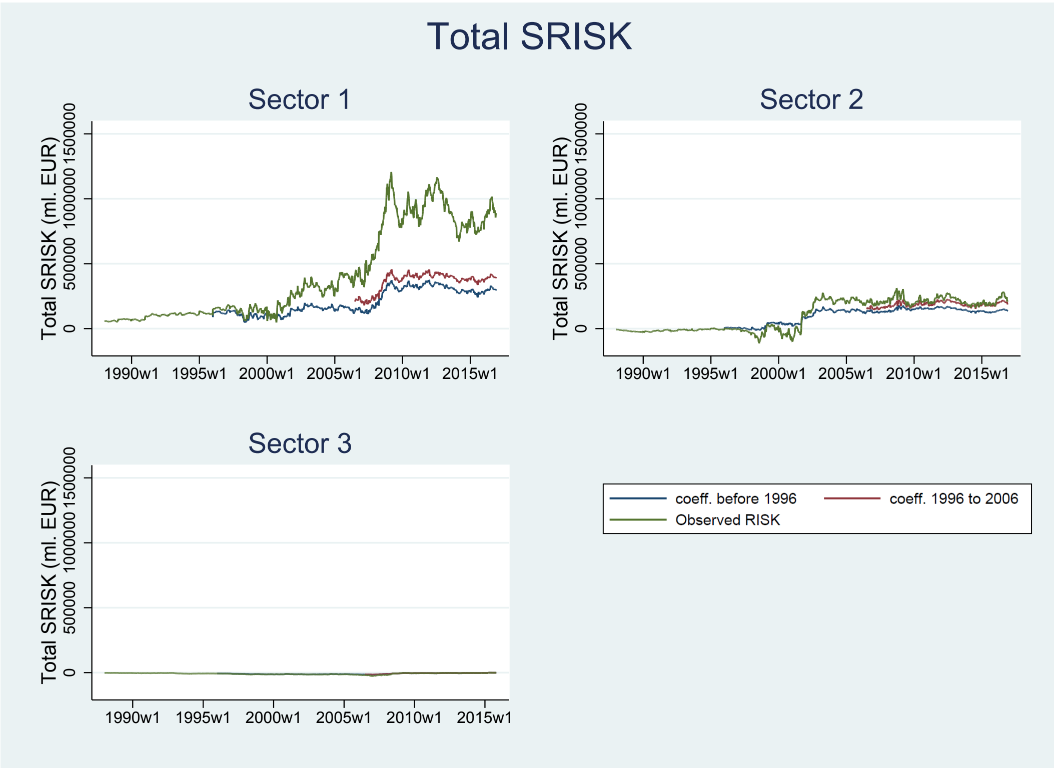

Figure 8: Evolution of historical total sectoral SRISK vs. counterfactual total sectoral SRISK. The Figure presents the evolution of the historical total SRISK compared with the estimated forecasted SRISK in case of no Market Risk Amendment (blue line) and no Basel II accord (red line). We average SRISK according to the financial sector: 1. banks and diversified institutions, 2. insurance companies, 3. real estate. We estimate SRISK using the dynamic two-stage model as Equation 1 in two sub-periods: i) before any internal models were available (prior to 1996) and ii) prior to the implementation of internal credit risk models (1996-2006).

the risk exposure around the turn of the millennium, suggesting that the market risk amendment might have been helpful in improving risk management for European banks on average.[13] These observations are in line with the original intentions of the Basel Committee even though they appear quantitatively small.

Most strikingly, however, in the run-up to the Great Financial Crisis our results suggest that internal models contributed largely to the lack of resiliency of European banks. Our simulations suggest that internal models contributed largely to amplify the capital short-fall in in 2008-9 by a factor of two. In fact both, internal models for market risk and for credit risk did contribute to a massive amplification of exposure to systemic risk in the European banking system. After 2014, we observe a significant reduction in aggregate systemic risk, but well above the levels of the Great Financial Crisis. It remains worrisome though that despite improved supervision the capital shortfall remains at the levels of the Great Financial Crisis of an average of about 5 billions of Euros per bank. There is no indication of a normalization of the capitalization of European banks to pre-crisis levels despite serious regulatory attempts and despite the creation of Banking Union in order to improve supervision of Eurozone banks.

In our dataset can apply the same analysis also for other financial institutions such as insurance, real estate and diversified financials. We can use this extra information to test for identification of the behavioural changes. The use of internal models within Basel regulation should not directly affect non-bank financial intermediaries. However, there might be indirect effects to the extent that regulations affects inter-modal competition and business models across sectors.

Figure 8 provides the historical and estimated evolution of SRISK for the various financial subsectors: banks, insurance companies and real estate. In line with our expectation the figure clearly illustrates that there are virtually no relations of the two policy instruments on the real sector. However, and somewhat surprisingly, we discover small spill-overs of the market risk amendment into the insurance sector and quantitatively even smaller spill-overs for Basel II. Interestingly, at the turn of the century the insurance sector was even more resilient than predicted. This reflects trading and hedging activities between banks and the insurance sector after implementation of the market risk amendment. Since credit risk plays a smaller role in th insurance sector it may not surprise to find that Basel II had a minimal impact on the resiliency of the insurance sector.[14] Overall this evidence suggests that internal models did essentially affect bank behaviour, insurance behaviour only to a small extent by the market risk amendment, and the real estate sector not at all. This finding adds confidence to our interpretation that internal models did induce the adoption of less resilient business models in the banking sector.

6.2 Impact of IRB-Models

Further support for a causal relation between internal models and the build-up in capital shortfall, and hence one component of systemic risk, can be derived from an analysis of behavioural changes around the implementation dates of the internal models for credit risk. We apply a difference-in-difference approach to estimate the effect of IRBA models on the systemic risk exposure of the banks

[13]This is in line with the short-lived reduction in SRISK after the implementation of the internal market risk models in 1996 (see Figure 3).

[14]See Gehrig, Iannino (2018) for a detailed analysis of the spill-overs from banking regulation to the insurance sector and the resiliency of the insurance sector.

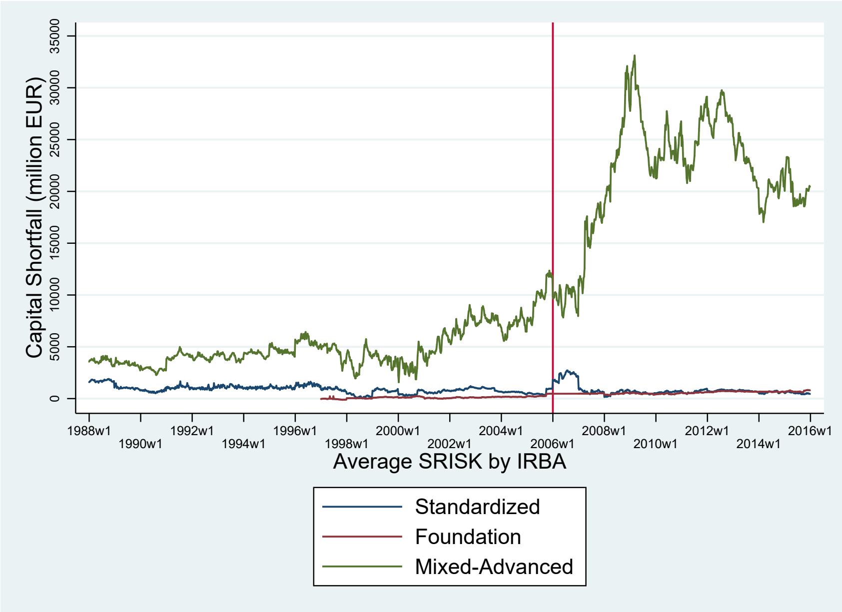

Figure 9: Credit Risk Internal Models and SRISK. We report the evolution of the daily estimated SRISK (Equation 13), distinguishing for the usage of credit risk internal models (IRBA). The blue line represent the behaviour of systemic risk before the introduction of Basel 2. After June 2006 (red vertical line), we distinguish between banks using the regulatory standardized approach (red line), the foundation approach (green line) and the banks using the mixed or advanced approaches (blue line). We report a central moving average of 1 year.

opting for the more sophisticated internal models option. Hence, we consider treatment as the implementation of IRBA for credit risk, so that treated banks are those that use either foundation or mixed/advanced internal models, while the untreated banks are the ones applying the standardized regulatory approach. We apply a Propensity Score Matching in order to assign comparable control banks to each treated institution.

A naive comparison of SRISK is shown in Figure 9. We observe how banks that opted for advanced or mixed IRBA after 2006 always had a higher level of SRISK. However, thie systemir risk exposure sharply increases after Basel II allows them to use IRBA.[15]

Moreover, banks using IRBA always tend to have a higher correlation with the market return and higher market capitalization in the overall time series (10). We will therefore use these variables as observable characteristics to match treated versus untreated firms, besides lagged SRISK, Zscore, and Market-to-Book.

Further support for your choice of propensity score matching is provided by the change in business models incentivized by Basel II. Because of data limitations in SNL bank coverage, we have to restrict our analysis to observations from 2005 onwards.

Scrutinizing bank characteristics (Figure 11), we observe that banks that use a mixed or advanced

[15] The seemingly strange pattern of foundation-IRBA is due to the fact that banks entered gradually into internal modelling, therefore the foundation approach was a first intermediate step for banks that consequently moved on to implement advanced approaches.

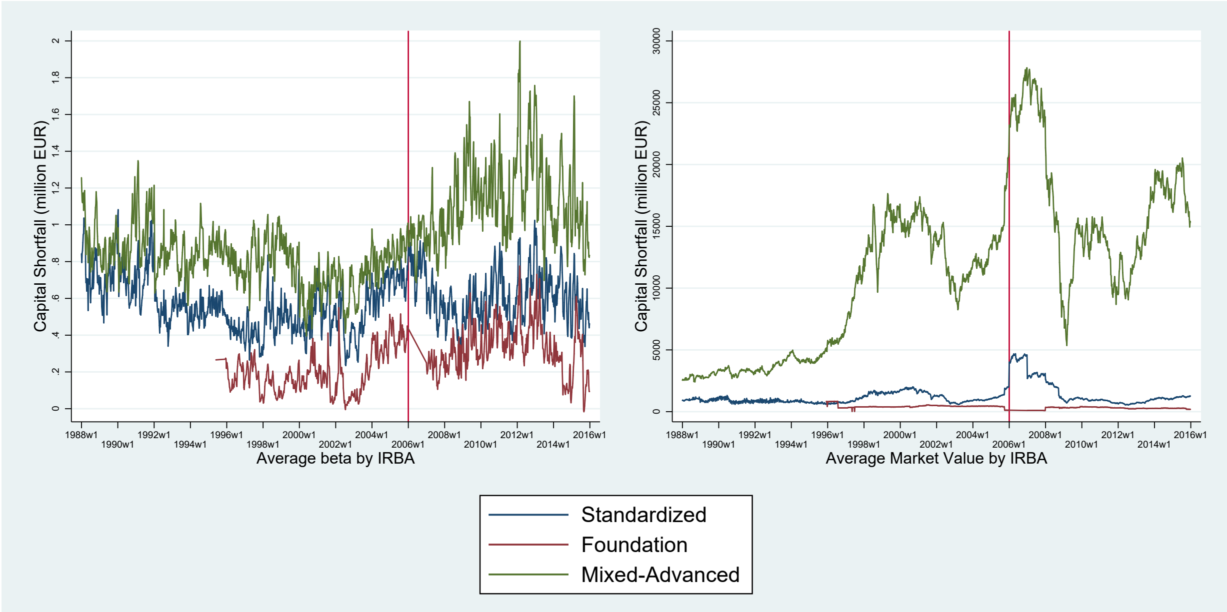

Figure 10: Credit Risk Internal models, Beta and Market Value. We report the evolution of the daily estimated SRISK (Equation 13), distinguishing for the usage of credit risk internal models (IRBA). The blue line represent the behaviour of systemic risk before the introduction of Basel 2. After June 2006 (red vertical line), we distinguish between banks using the regulatory standardized approach (red line), the foundation approach (green line) and the banks using the mixed or advanced approaches (blue line). We report a central moving average of 1 year.

approach tend to be the largest firms in terms of Tier-1 capital. However, at the same time they exhibit the strongest increase in their Non-Performing Loans ratios, while, seemingly paradoxically, holding the lowest level of total equity. In terms of risk weights their trajectory follows closely the trajectory of banks with the standardized approach after 2010 but are well below before.

Applying a difference-in-difference analysis, we discriminate between treated versus control banks, before and after Basel II implementation on January 2006. In order to estimate the counterfactual and reduce the selection bias, we identify a control group by the kernel Propensity Score Matching method developed by Rosenbaum et al. (1983). Based on the above observations we run a probit regression to estimate the probability of implementing IRBA models given the first difference in SRISK, market beta, z-score, market capitalization, and country. A propensity score is then assigned to balance the treated and the comparison groups.

Next, we estimate a difference-in-differences weighted regression, where observations are weighted to ensure that each group reflects the covariate distribution in the pre-Basel II period. The outcome variable is the first difference in SRISK, and we include the covariates we have previously found as important drivers of SRISK as Beta, z-score, CISS, market return, LT interest rates, country and a dummy identifying the 2008 crisis and post crisis:

$$DSRISK_{it} = \sigma_0 + \sigma_1 IRBA + \sigma_2 BaselII + \sigma_3 BaselII * IRBA + \gamma_k L.Z_{it} + \sum_q \gamma_q L.X_t + \varepsilon_{it} \quad (5)$$

where IRBA is the dummy variable identifying banks with advanced or mixed credit risk internal models, Basel II is the time dummy capturing changes after the implementation of Basel II, and

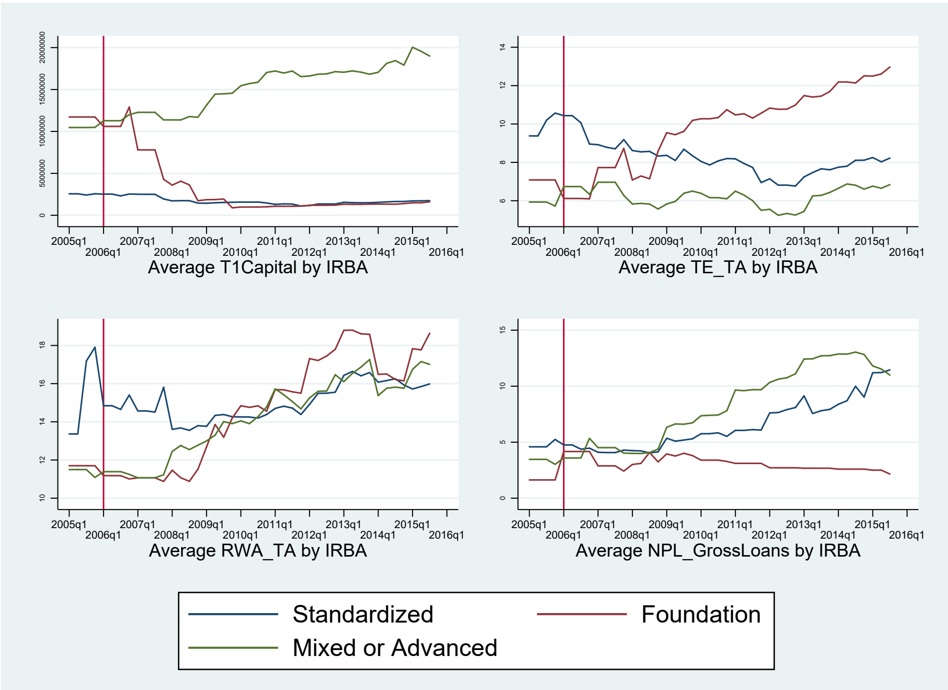

Figure 11: Credit Risk Internal Models and Total Assets. We report the evolution of quarterly book values of assets, as Tier 1 Capital (top left frame), leverage ratio such as total equity over total assets (top right), estimated market Beta (bottom left) and Non-Performing loans over Gross Loans (bottom right), distinguishing for the usage of credit risk internal models (IRBA). We average in groups based on the usage of credit risk internal models (IRBA). After June 2006, we distinguish between banks using the regulatory standardized approach (blue line), the foundation approach (red line) and the banks using advanced or mixed approaches (green line).

Basel II * IRBA is the interaction term identifying IRBA banks after June 2006. X_t and Z_{it} include all the previous bank and market regressors.

The difference-in-differences parameter is therefore:

$$\widehat{\sigma_3} = (\overline{SRISK}_{IRBA,post} - \overline{SRISK}_{IRBA,pre}) - (\overline{SRISK}_{nonIRBA,post} - \overline{SRISK}_{nonIRBA,pre}) \quad (6)$$

This method allows us to remove both potential biases in the post-Basel period between the treated and the control groups that could result from permanent differences between banks, and potential biases from comparisons over time in the treatment group that could result from other changes.

We conclude with a difference-in-differences analysis and report the results on the mean regression. The treated group comprises banks that did implement internal credit risk models after the regulatory option is made available by Basel II in June 2006. We first use propensity score matching (PSM) to weight observations such that the treated group reflects the distribution of covariates in the pre-Basel period. We report both the results for the probit regression for the PSM and the difference-in-differences estimation in Table 3. We choose the bank-characteristics that were used before throughout our analysis to identify control banks by lagged SRISK, market beta, Zscore, market-to-book and market value. All these characteristics appear to importantly affect the choice of implementing internal models, in line with the probit regression results in frame A.

The PSM provides the weights for the weighted diff-in-diffs regression. The results strongly support our hypothesis that exposure to systemic risk is largely driven by the use of internal credit risk models. While there are no significant differences in SRISK between treatment and control groups prior to the implementation of Basel II standards, we find strong and significant differences in risk exposure after their introduction in 2006. In the follow-up period, we see that institutions that have chosen to implement credit risk models as either advanced or mixed approaches, have increased more than tenfold their exposure to systemic risk in the post-Basel II period compared to the peer group.

7 Role of Market Information for Banking Supervision

An attractive feature of market based risk measures is their control for market feedback. Regulatory institutions and supervisors, however, typically focus on information about individual institutions and, hence, idiosyncratic risk such as typically embodied in book values. Also the Basel capital regulation focuses on book rather than market values. This regulatory approach, while facilitating the analysis of single institutions by separating them from market developments, is not helpful in a systems context, since the very foundations of systemic risk are tied to the notion of market feedback. Bank runs do occur because of depositors' (self-fulfilling) fears about other depositors running. Contagion effects occur, whenever insolvencies of single institutions cause knock-on insolvencies of connected, but otherwise healthy, financial institutions. Accordingly, discrepancies between book and market values may contain important systemic information to which supervisors (and regulators) should not cast a blind eye.

In order to illustrate the informational content of the market based capital shortfall measure SRISK, we provide a brief discussion of two systemic European banks that entered into different trajectories during the Great Financial Crisis, Deutsche Bank and Union Bank of Switzerland (UBS)

Table 3: PSM and Diff-in-Diff

A. Probit regression

IRBA01	Coef.	z	p-value
L.Beta	7.62E-01	27.07	0
Zscore	1.01E-02	8.19	0
Market Value	9.86E-05	46.18	0
coun_3	-1.43522	-13.81	0
coun_5	-2.41E+00	-25.88	0
coun_7	-9.19E-01	-9.67	0
coun_8	-1.16008	-12.55	0
coun_9	-0.67934	-6.38	0
coun_11	-2.95999	-26.89	0
Constant	0.26781	2.97	0.003

Pseudo R2 = 0.4411

B. Difference-in-difference estimation

Outcome var.	Δ SRISK	t	p-value
Baseline:			
Control	128.964		
Treated	181.990		
Diff (T-C)	53.026	1.37	0.171
Follow-up:			
Control	175.579		
Treated	303.758		
Diff (T-C)	128.179	3.56	0.000***
Diff-in-Diff	75.153	1.79	0.074*

[a] This table reports the results from the Propensity Score Matching and the difference-in-difference analysis on banks with internal credit risk models (Advanced or mixed approaches) versus comparable banks without IRBA, before and after the regulatory change in 2006. Propensity Score is estimated via a probit regression, where the probability of implementing IRBA is explained by lagged SRISK, market beta, Zscore, Market-to-Book, and market capitalization. We report robust standard errors, clustered per firm. ***0.01; **0.05; *0.10.

(Figures 12). While UBS had to be rescued by the tax payers in 2007, Deutsche Bank succeeded to (narrowly) escape the need of government support in 2007-8. In the respective SRISK trajectories we identify similar pre-crisis developments. Both banks had accummulated a pre-crisis shortfall of about 60 bill. Euro according to our crisis definition. During the crisis the measure shot up to about 160 bill. Euro in the case of Deutsche Bank, while in the case of UBS the tax payer intervened and the measure only increased to about 100 bill. Euro. In 2010 the shortfall measures declined in both cases but remained considerable above pre-crisis level until the European Sovereign Crisis hit, increasing the short fall again for both banks. But even after 2013 in the case of Deutsche Bank the capital shortfall basically remained at level of 2009, considerably above the pre-crisis level of 2007. In contrast UBS succeeded in reducing capital shortfall to pre-crisis levels of 2007 and even below.

The troubles of Deutsche Bank after the leakage of hefty penalties in the United States in September 2016 are clear evidence that capital shortfall is strongly correlated with lack of investor confidence and a high degree of stock market volatility, essentially due to worries about the bank's resilience. Quite differently, UBS seems to stay out of trouble quite comfortably despite the realizations of operational risk also on their side.

European supervisors tend to take the view that markets may be over-reacting to bad news causing market-to-book values to be excessively depressed. They seem to be essentially satisfied by what they consider serious attempts of Deutsche Bank - and other systemic banks - to rebuild *book values* of regulatory tier-1 capital [16]. This lack of drive is somewhat surprising, since according to Gandhi et al. (2015, 2016) and Kelly et al. (2016) bank equity is cheap particularly for the large banks. Rather the ECB tends to be more concerned to harmonize supervisory procedures for smaller banks than to recapitalize the ailing systemic banks in Europe (see Gehrig et al. 2016).

The case of UBS is an interesting case study, since i) Switzerland is over-complying with Basel III standards, and ii) UBS is over-complying with Swiss standards. And in fact, market-to-book recovered for UBS to essentially normal values, while in the case of Deutsche Bank, market-to-book remains on a long run decline well below .5.[17] The case of UBS demonstrates that it is possible to rebuild market confidence and, thus, market valued capital, if the recapitalization is done seriously enough. Obviously, it is very costly to undo the massive stock repurchases in the run-up to the Great Financial Crisis, but rebuilding confidence requires serious and similarly massive commitment. Market values are important indicators of market confidence and trust (Gehrig, 2013), and, hence, relevant information also for supervisors.

[16] See e.g. Carney, 2016, Dombrovskis, 2016 and Nouy, 2016

[17] In September 2016 market-to-book for Deutsche Bank even fell as low as .10.

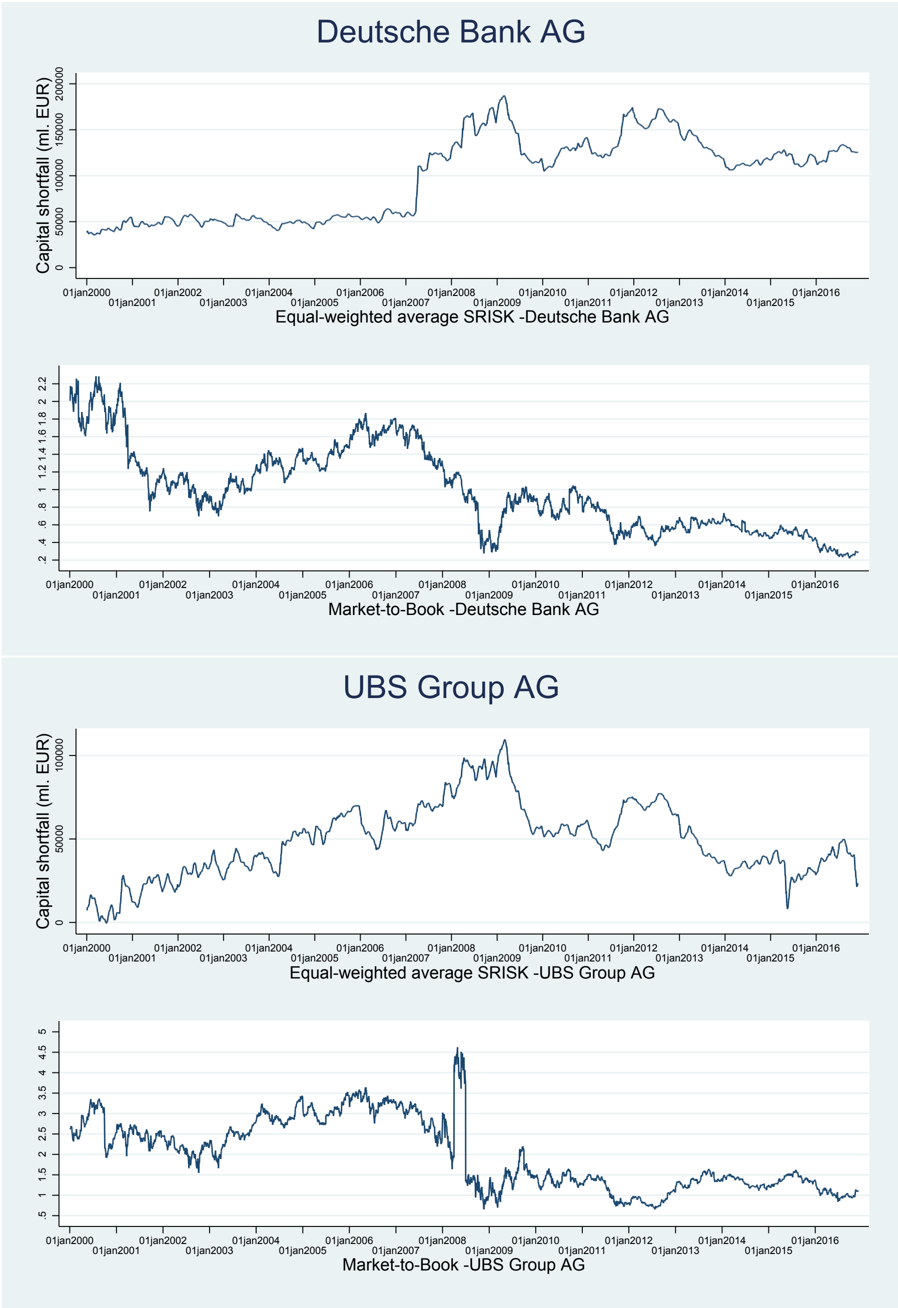

Figure 12: Cross-sector variation of systematic risk. The Figure presents the evolution of the SRISK and Market-to-Book of Deutsche Bank and UBS.

8 Relation to the Literature

In retrospect our empirical results may not come as a big surprise. Academics have always been critical of the Basel process of Capital Regulation already at the time of inception of the various regulations. Hellwig (1995) was worried about correlations between market and credit risk not being properly addressed by Basel I regulation.[18] Danielson, Embrechts, Goodhart, Keating, Münnich, Renault and Shin (2001) raised serious concerns about the endogeneity of risks not being addressed at all within the Basel II framework, suggesting that Basel II might unintentionally and paradoxically even reduce safety and soundness of the banking system.[19]

But also on a purely methodological level the Basel approach attracted criticism of not accounting properly for extreme events and tail risk in particular. Notably, Eberlein and Keller (1995) demonstrate that hyperbolic Levy processes track real world market data far better than Gaussian processes. Building on this insight Eberlein et al. (1998) determine value-at-risk estimates and demonstrate that they tend to be much larger than under normality assumptions. At the standard 99%-VAR, typically Levy models would require double the amount of capital than Gaussian models would impose.[20]

While the academic literature has focused on methodology and on developing new systemic risk measures, few studies exist about the market reactions to Basel-driven regulation in the banking industry. One important study is Wagster (1996) who has linked the Basel process to the competitiveness of banks across countries. In particular, he identified market reactions at various stages of the discussion about Basel I reforms. He shows that the Basel process can be viewed as a political bargaining process between national regulators; many agreements by Japanese authorities, in particular concerning the regulatory treatment of hidden reserves, were elicited by concessions to the Japanese banking sector that were subsequently capitalized in market prices and can be measured accordingly. To the best of our knowledge our work is the first systematic long-run evaluation of the effect of the Basel process of capital regulation on the safety and soundness of banking systems.

Concerning internal credit risk models we confirm and extend the results of Behn, Haselmann and Vig (2016) and Mariathasan and Merrouche (2014) about the limitations of model-based regulation. We also find that internal models are used to systematically reduce - or even manipulate - risk weights. However, unlike the earlier contributions we also compare and assess the relative contributions of credit risk models to market risk models and find differential effects. Not surprisingly for credit institutions, the impact of credit risk models quantitatively dominates the effects of market risk models. Hence, we confirm that internal credit risk models indeed are the main driver of systemic risk relative to all the other policy stages.

An important contributing result to our analysis is the consistently negative effect of the policy rate of monetary policy on the systemic risk exposure throughout the whole distribution of banks. Thus expansionary monetary policy induces the implementation of riskier business models in the banking sector, and, hence, a reduction in resiliency and stability. But unlike internal models the policy rate has a pretty much uniform affect across the whole distribution.

[18] On a Panel Discussion on Capital Requirements for Market Risks Based on Inhouse Models in 1995 Hellwig (1996) suggests "that ten years later there may well be another panel, this one devoted to problems of quality assessment for inhouse models of credit risk and that a key question is what will happen to banks and banking systems in the ten intervening years". History has replaced that panel with a true field experiment in the 2007-8 crisis. So this paper can also be viewed as a response to Hellwig's (1996) request for an evidence-based evaluation of the internal model based approach to market risk.

[19] On the problem of neglecting the endogeneity of systemic risk see also Hellwig (2010).

[20] Incidentally, Eberlein et al. (1998) determine value-at-risk based capital for Deutsche Bank at more than double the amount required under the normality assumption of the market risk amendment (see their Table VIII).

Interestingly, we also observe a considerable build-up of systemic risk in the insurance sector. We can trace this evolution back beyond the time span of other studies (Berdin, Sottocornola (2015), IMF Global Stability Report, 2016), starting in 1996 with the Market Risk Amendment of the Basel Accord, and increasing in size and relevance thereafter. This findings are consistent with the existence of significant spillover effects from the banking sector to the insurance, following the change in regulation in the banking activity (Gehrig, Iannino, 2018).

9 Conclusion

We document a steady increase in the systemic risk exposure of European banks as measured by the capital shortfall measure SRISK within the past 30 years, despite intensive regulatory attempts to impose a floor on capital in a long process of minimum capital regulation. This finding is complemented by the observation of an increase in individual banking risk as well as systemic risk for a number of other widely used systemic risk measures. The lion's share of the increase occurs in the highest quintile of the size distribution of banks. For almost half of the banks in our sample, and certainly for the lower two quintiles, the various risk measures are increasing moderately or even remain roughly constant over the past 30 years.

While the Basel process of capital regulation was designed to increase the stability and safety of the global banking system, our evidence suggests that it did not achieve this goal in its first three decades of operation for European banks. From the perspective of systemic risk measures, the Basel process has been more effective for smaller banks. But even there it did not significantly reduce systemic exposures or contagion risk. For the largest quantiles of banks, internal models might have provided strong incentives to carve out equity and, thus, reduce in-house resiliency. The evidence demonstrates that those incentives were exploited and the resiliency of large and systemically important European banks became greatly impaired at the onset of the Great Financial Crisis. To the extent that most of the large banks did engage in this activity of reducing their capital buffers, overall bank capital became scarce, generating systemic concerns for the whole banking sector. But even after 2008 most individual - and thus aggregate - SRISK scores did not retreat to pre-crises levels or even below.[21]

Controlling for bank balance sheet variables, the standard drivers of bank stock prices and macroeconomic indicators[22], our structural analysis of the drivers of SRISK strongly suggests that internal risk models were chosen strategically. Similar results have been derived by Behn, Haselmann and Vig (2016) on a sample of German banks and Colliard (2015). The strategic use of internal models is one source of the depletion of bank equity (Admati, Hellwig, 2013). Ironically, these equity carve-outs were one way of increasing return on equity through extensive stock repurchases prior to - and even after - the Great Financial Crisis at a time when the cost of bank equity was actually low, and strengthening capitalization and resiliency would have been relatively cheap (in historical

[21] This observation is consistent with attempts of ECB researchers (Homar, Kick, Salleo, 2016) trying to empirically validate the ECB policy of focusing on particular on the European ECB and EBA stress scenarios rather than focusing on individual and aggregate capital shortfall for the Euro area as suggested for example by Acharya, Engle and Pierret (2014).

[22] While we cannot completely rule out omitted variables, we make a large attempt to include all the known drivers of stock prices that crucially affect our endogenous variable SRISK plus additional country-specific macro-economic indicators. Moreover, the cross-sectoral heterogeneity does contribute importantly to identifying causal relationships between regulatory variables and SRISK. In addition we perform both a counter-factual simulation and a diff-in-diff analysis.

context).[23]. Of course, this observation may simply constitute a reflection of the leverage ratchet effect. (see Admati et al. (2016)).

On the basis of our analysis it is not necessarily that capital rules per se were insufficient; it is rather the possibility to reduce effective capitalization by means of complex risk models under supervisory approval that causes the lack of resiliency. Our findings accord well with Miles et al. (2012). They seem to contradict Jackson (2015) in the sense that simple models, even at sub-optimal levels in terms of efficiency, may be more suitable to limit risks and, hence, safeguard resiliency.

It is not evident that these outcomes should be viewed as unintended consequences of the Basel process of capital regulation. Rather public warnings about such outcomes had dutifully and rigorously been voiced by leading academic researchers. Notably Danielson et al. (2001) raise serious concerns that the neglect of endogeneity of systemic risk could turn into an unintended build-up of major systemic risk within the Basel II approach. However, the political economy of the Basel process might have succumbed too much to industry interests in reducing the bite of the standard approach by introducing generous options to determine regulatory capital with the help of their own internal models.

While the political support for the use of internal models still is unbroken, the recent debate on the conclusion of Basel III also reflects more critical perspectives on self-regulatory instruments, and, hence, the need of limiting their potential misuse. The Basel Committee's Consultative Document on credit risk models (Basel Committee on Banking Supervision, 2016) explicitly proposes to remove this self-regulatory option for exposures that do not allow for sufficiently reliable estimates, such as low-default exposures. This recommendations accords well with our empirical findings presented above. Surprisingly, in finalizing the Basel III agreement it was the European supervisors who were reluctant in curbing the use of mixed and advanced IRBA-models, while the original proponents of internal models under Basel II, namely the U.S. tried to phase them out.[24]

We also suggest that, by concentrating on formal fulfilment of regulatory rules based on book values, regulators missed a pro-social role in interpreting (negative) market feedback. Relying on rules based on book values only, neglects social feedback and market expectations. However, trust and confidence are key in the banking industry, but they are notoriously difficult to measure. Hence, market based risk measures are one simple step towards taking into account market reactions, trust and confidence, and hence systemic market feedback. This is potentially crucial information and supervisors should be challenged to explain more when and why they disregard market information.[25] After all, supervision attains an important role to correct potential misbehavior only in market economies. This argument assumes the existence of a sufficiently high degree of trust in the operation of markets after all. If this trust cannot be assured in normal periods, why not economize on bureaucracy and centralize the whole banking system?

[23] Baron and Xiong (2014) provide a behavioural explanation based on over-optimism.

[24] The conclusion of Basel III at the Santiago de Chile Summit in November 2016 failed because of disagreement about the proper output floor. While the U.S. insisted on a minimal role for internal models with an output floor of above 80% the European supervisors pushed for an output floor of below 70%. The output floor provides a limit by which internal models can undercut the risk weights implied by the standard approach. In November 2017 a compromise was found at an output floor of 72.5%.

[25] This argument is not saying that there is no mispricing in markets. However, under normal conditions mispricing should be a short term problem. In the long run markets should converge to fair valuations. For example, a market-to-book anomaly may occur for short periods; but when it persists for years or decades, the underlying sources of the anomaly may be important to remedy.

Our analysis also uncovers disconcerting effects of monetary policy on banks' contribution to systemic risk. This is particularly true for the less risky and typically smaller banks. Hence, we empirically verify that a low-growth environment creates incentives for risk-taking, and, therefore, an increase both in contagion risk and exposure to systemic risk. Accordingly, under the current regulatory framework, Quantitative Easing, through its effect on interest rates, might tend to contribute to undermining the stability and soundness of the European banking system.[26] Interestingly, these concerns do not affect the most systematically risky banks, which are tightly supervised in the first place.

There are even wider implications of the Basel process of capital regulation beyond the banking industry on the whole financial sector. For example, the build-up of systematic risk in the insurance sector (Gehrig, Iannino, 2018), while not as dramatic as in the banking sector, also significantly moves upwards with a structural break around 1996. Possibly these developments also exhibit unintended consequences across markets and industries: long-term lending is increasingly given up by banks[27] and taken over by the insurance sector. Hence, a final evaluation of the welfare consequences of the Basel process of capital regulation requires an analysis whole financial sector in order to not only account for market feedback, both in the regulated as well as the unregulated segments, but also for substitution effects and their implications on complementary activities. We leave this for future research.

We leave for future research also the interaction between capital regulation and Banking Union. It is too early for a final judgement of Banking Union on the most systemic banks. However, at this stage we cannot detect any decline in the systemic risk scores for the banks under direct ECB supervision. Certainly, their SRISK remain well above the 2008 levels still in 2016.

We end with the observation that the build-up in systemic risk in the financial sector entails considerable tail risk for the macro economy, which has been identified as one likely channel for seculiar stagnation (e.g. Kozlowksi, Veldkamp, Venkatesvaran, 2015).[28] To the extent that one subscribes to this argument, it is true that the Basel process has contributed to permanently enhancing tail risk. Thus, under this view, real effects of the resulting equity carves out in European and global banking systems can be seen contributors to the decline in long-term investment growth. The *missing recovery* after the Great Depression (Summers, 2016, Teulings Baldwin, 2014), unfortunately, correlates strongly with high levels of systemic risk, particularly for the largest, and, presumably, most efficient financial institutions worldwide.

A robust recommendation suggested by our work for policy makers and supervisors implies that all attempts to fix the capital shortfall and, hence, exposure to systemic risk of European banks have not been determined enough so far as to rebuild pre-crisis resiliency.[29]

[26]Our findings suggests that Quantitative Easing would require complementary supervisory instruments to control adverse risk-taking incentives. In the case of Europe such complementary control was not effective for the period of our study.

[27]On the shortening of banks' planing horizon see also Boot and Ratnovski (2016).

[28]Kozlowski et al. (2015) argue that rare event realizations of tail risk have changed long term beliefs and expectations. Analysing credit spreads Füss et al. (2016) find similar evidence of changing risk perceptions in the U.S. corporate debt market.

[29]As mentioned in section 7, in our sample only very few banking institutions have succeeded in recapitalizing sufficiently in order to rebuild resiliency to pre-crisis levels such as UBS outside the Euro-area.

10 References

Acharya, V., L. Pederson, P. Phillipon and M. Richardson (2017): Measuring Systemic Risk, *Review of Financial Studies*, 30(1), 2-47.

Acharya, V., R. Engle and D. Pierret (2014): Testing Macroprudential Stree Tests: The Risk of Regulatory Risk Weights, *Journal of Monetary Economics* 65, 36-53.

Acharya, V., R. Engle and M. Richardson (2012): Capital Shortfall: a new Approach to Ranking and Regulating Systemic Risks, *American Economic Review, Papers & Proceedings* 102(3), 59-64.

Admati, A., P. DeMarzo, M. Hellwig and P. Pfleiderer (2016): The Leverage Ratchet Effect, Stanford School of Business WP 3029.

Admati, A. and M. Hellwig (2013): *The Bankers' New Clothes*, Princeton University Press, Princeton.

Adrian, T. and M. K. Brunnermeier (2016): CoVaR. *American Economic Review* 106(7), 1705-1741.

Allen, L., T. Bali and Y. Tang (2012): Does Systemic Risk in the Financial Sector Predict Future Economic Downturns? *Review of Financial Studies* 25(10), 3000-3036.

Ayadi, R., G. Ferri and V. Pesic (2016): Regulatory Arbitrage in EU Banking: Do Business Models Matter?, IRCCF Working Paper, HEC Montreal.

Bahaj, S. and F. Malherbe (2016): A positive analysis of bank behaviour under capital requirements, CEPR-DP 11607.

Baker, M. and J. Wurgler (2015): Do Strict Capital Requirements Raise the Cost of Capital? Bank Regulation and the Low Risk Anomaly, *American Economic Review* 105(5), 315-320.

Barnes, M. and J. Lopez (2006): Alternative measures of the Federal Reserve Banks' cost of equity capital, *Journal of Banking and Finance* 30, 1687-1711.

Beltratti, A. and R. Stulz (2012): The Credit Crisis Around the Globe: Why Did Some Banks Perform Better?, *Journal of Financial Economics* 105, 1-17.

Baron, M. and W. Xiong (2014): Credit Expansion and Neglected Crash Risk, working paper, Princeton.

Basel Committee on Banking Supervision (1988): International Convergence of Capital Measurement and Capital Standards, Basel, July 1988.

Basel Committee on Banking Supervision (1996): Amendment to the Capital Accord to Incorporate Market Risks, Basel, January 1996.

Basel Committee on Banking Supervision (2004): Amendment to the Capital Accord to Incorporate Market Risks: A Revised Framework, Basel, June 2004.

Basel Committee on Banking Supervision (2016): Consultative Document - Reducing variation in credit risk-weighted assets: constraints on the use of internal model approaches, Basel, March 2016.

Behn, M., R. Haselmann and V. Vig (2016): The Limits of Model-Based Regulation, ECB Working Paper No. 1928, Frankfurt, July 2016.

Benoit S., Colletaz G., Hurlin C., C. Perignon, (2013): A Theoretical and Empirical Comparison of Systemic Risk Measures, HEC Paris Research Paper No. FIN-2014-1030.

Brownlees D. and R.F. Engle (2012): Volatility, correlation and Tails for Systemic Risk Measurement, working paper.

Berdin, E. and M. Sottocornola (2015): Insurance Activities and Systemic Risk, SAFE Working Paper 121, Frankfurt.

Berg, T. and P. Koziol (2017): An analysis of the consistency of banks internal ratings, *Journal of Banking and Finance*, 78, 2017, 27-41.

Blinder, A. S. (1973): Wage discrimination: Reduced form and structural estimates, *Journal of Human Resources* 8, 436455.

Boot, A. and L. Ratnovski (2016): Banking and Trading, *Review of Finance*, 20(6), 2219-2246.

Boyd, J. H. and Runkle D. E. (1993): Size and performance of banking firms: Testing the predictions of theory, *Journal of Monetary Economics* 31(1), 47-67.

Brownlees D. and R.F. Engle (2017): SRISK: A Conditional Capital Shortfall Measure of Systemic Risk, *Review of Financial Studies* 30(1), 48-79.

Calomiris, C. and D. Nissim (2014): Crisis-related shifts in the market valuation of banking activities, *Journal of Financial Intermediation* 23, 400-435.

Carney, M. (2016): Redeeming an unforgiving world, Speech at G-20 Meeting, Institute of International Finance, 26. February, Shanghai.

Colliard, J.-E. (2015): Strategic Selection of Risk Models and Bank Capital Regulation, working paper.

Danielson, J., P. Embrechts, C. Goodhart, C. Keating, F. Münnich, O. Renault, and H.S. Shin (2001): An Academic Response to Basel II, FMG Special Paper 130.

Demirguc-Kunt, A., Detragiache, E. and O. Merrouche (2013): Bank capital: Lessons from the Financial Crisis, *Journal of Money, Credit & Banking* 45, 1147-64.

Dombrovskis, V. (2016): Embracing Disruptions, Speech at European Banking Confederation, 29. September, Brussels.

Driscoll, J. C., and A. C. Kraay (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics* 80, 549-560.

Eberlein, E. and U. Keller (1995): Hyperbolic distributions in finance, *Bernoulli* 1, 281-299.

Eberlein, E., U. Keller, K. Prause (1998): New insights into smile, mispricing and value at risk: the hyperbolic model, *Journal of Business* 71, 371-405.

Engle, R.F. (2002): Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models, *Journal of Business and Economic Statistics*, vol. 20, p.339-350.

Engle, R.F., E. Jondeau and M. Rockinger (2015), Systemic Risk in Europe, *Review of Finance* 19(1), 145-190.

Fama E. and French K. (1993), Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33 (1), 3-56.

Fiordelisi, F., and D. Marques-Ibanez (2013): Is bank default risk systematic?, *Journal of Banking and Finance* 37 (6), 2000-2010.

Firpo, S., Fontin, N. and T. Lemieux (2009): Unconditional Quantile Regressions, *Econometrica* 37 (6), 2000-2010.

Füss, R., T. Gehrig and P. Rindler (2016): Changing Risk Perception and the Time-Varying Price of Risk, *Review of Finance* 20(4), 1549-1585.

Gandhi, P. and H. Lustig (2015): Size anomalies in bank stock returns, *Journal of Finance* 70, 733-768.

Gandhi P., H. Lustig and A. Plazzi (2016): Equity is Cheap for Large Financial Institutions: The International Evidence, NBER Discussion Paper 22355, Boston.

Gehrig, T. (1995): Capital Adequacy Rules: Implications for Banks' Risk Taking, *Swiss Journal of Economics and Statistics* 131 (4/2), 747-764.

Gehrig, T. (1996): Market Structure, Monitoring and Capital Adequacy Regulation, *Swiss Journal of Economics and Statistics* 132 (4/2), 685-702.

Gehrig, T. (2013a): Capital, Trust and Competitiveness in the Banking Sector, CEPR Discussion Paper 9348, London.

Gehrig, T. (2013b): Capital, confiance et compètitivitè dans le secteur bancaire, *Revue d'Economie Financière* 112 (Les systèmes bancaires europèens (2)), 175-193.

Gehrig, T. and M.C. Iannino (2018): Bank Capital Regulation and Systemic Risk in the Insurance Sector, *Journal of Financial Economic Policy* 11:2 (forthcoming).

Gehrig, T., M. Messori, A. Nogueira Leite, A. Sapir, D. Schoenmaker, S. Steffen, P. Tibi, D. Vegara and N. Véron (2016): European banking supervision: the first eighteen months, Bruegel Blueprint Series 25, Brussels.

Giglio, S., B. Kelly, S. Pruitt (2016): Systemic Risk and the Macroeconomy: An Empirical Evaluation, *Journal of Financial Economics* 119:3, 457-471.

Glosten, L., R. Jagananthan and D. Runkle (1993): On the Relation between the Expected Value and the Volatility of Nominal Excess Returns on Stocks, *Journal of Finance* 48(5), 1779-1801.

Goodhart, C. (2011): *The Basle Committee of Banking Supervision: A History of the Early Years 1974-1997*, Cambridge University Press, 2011.

Hakenes, H. and I. Schnabel (2011): Bank Size and Risk Taking under Basel II, *Journal of Banking and Finance* 35, 1436-1449.

Hellwig, M. (1995): Systemic Aspects of Risk Management in Banking and Finance, *Swiss Journal of Economics and Statistics* 131 (4/2), 723-737.

Hellwig, M. (2009): Systemic Risk in the Financial Sector: An Analysis of the Subprime Mortgage Financial Crisis, *De Economist* 157, 129-207.

Hellwig, M. (2010): Capital Regulation after the Crisis: Business as Usual?, Preprints of the Max-Planck Institute for Research on Collective Goods 2010/31.

Hellwig, M. and M. Staub (1996): Capital Requirements for Market Risks Based on Inhouse Models - Aspects of Quality Assessment, *Swiss Journal of Economics and Statistics* 132, 755-786.

Holl, D., Kremer, M., and Duca, M. Lo. (2012). A Composite Indicator of Systemic Stress in the Financial System. *ECB Working Paper Series*, March, no. 1426, p.151.

Homar, T., H. Kick and C. Salleo (2016): Making sense of the EU wide stress test: comparing with the SRISK approach, ECB working paper 1920.

IMF (2016): The insurance sector: Trends and systemic risk implications, *Global Financial Stability Report*, April.

Jackson, P. (2016): Simpler capital requirements versus risk-based - The evidence, *Banking reform*, SUERF Conference Proceedings, 2016/2.

Karolyi, A., J. Sedunov and A. Taboada (2017): Cross-Border Bank Flows and Systemic Risk, working paper.

Kelly, B., H. Lustig and S. Van Nieuwerburgh (2016): Too-systemic-to-fail: What option markets imply about sector-wide government guarantees, *American Economic Review* 106, 1278-1319.

King, M. (2009): The cost of equity for global banks: a CAPM perspective from 1990-2009, *BIS Quarterly Review*, September, 59-73.

Kozlowski, J., L. Veldkamp and V. Venaratesvaran (2015): The Tail that Wags the Economy: Belief-Driven Business Cycles and Secular Stagnation, NBER-Working Paper No. 21719.

Laeven, L., L. Ratnovski and H. Tong (2016): Bank size, capital, and systemic risk: an international comparison, *Journal of Banking & Finance*, 69(1), 25-34.

Maccario, A., A. Sirroni and C. Zazzara (2002): Is banks' cost of equity capital different across countries? Evidence from the G10 countries major banks, Libera Università Internazionale degli Studi Sociali (LUISS) Guido Carli, working paper, May.

Mariathasan, M. and O. Merrouche (2014): The manipulation of Basel risk weights, *Journal of Financial Intermediation* 23(3), 300-321.

Miles, D., J. Yang and G. Marcheggiano (2012): Optimal Bank Capital, *The Economic Journal*, 123, 1-37.

Nouy, D. (2016): Adjusting to new realities - Banking supervision and regulation in Europe, Speech at "European Banking Federation's SSM Forum", 6. April, Frankfurt.

Oaxaca, R. (1973): Male female wage differentials in urban labor markets, *International Economic Review* 14, 693709.

Plosser, M. and J. Santos (2014): Banks' INcentives and the Quality of Internal Models, Federal Reserve Bank of New York, Staff Report DP. 704.

Parente, P.M.D.C. and Santos Silva, J.M.C. (2016), Quantile Regression with Clustered Data, *Journal of Econometric Methods*, 5 (1), 1-15.

Rosenbaum, P.R. and Rubin, D.B. (1983), The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika*, 70 (1), 41-55.

Sarin, N. and L. Summers (2016): Have big banks gotten safer?, *Brookings Paper of Economic Activity*, Washington, September 2016.

Summers L. (2016): The Age of Secular Stagnation, *Foreign Affairs*, Mar./Apr. 2016, 2-9.

Teulings, C. and R. Baldwin (2014): Secular Stagnations: Facts, Causes and Cures, A VoxEU.org e-book.

Wagster, J. (1996): Impact of the 1988 Basle Accord on International Banks, *Journal of Finance* (52:4), 1321-1346.

Wuffli, P. (1995): Comment on the paper by Professor Hellwig: Systemic Aspects of Risk Management in Banking and Finance, *Swiss Journal of Economics and Statistics* 131 (4/2), 739-740.

11 Appendix

11.1 Risk Measures

11.1.1 Delta CoVaR

This measure starts from the estimation of an aggregate extreme loss in terms of Value-at-Risk, as the maximum loss of the market return within the α%-confidence interval, conditionally on some event $C(r_{it})$ observed for bank i:

$$Pr(r_{mt} \leq CoVaR_t^{m|C(r_{it})}) = \alpha \tag{7}$$

Using a quantile regression approach, we identify this distress event of firm i as a loss equal to its $(1-\alpha)$% VaR: $r_{it} = VaR_{it}(\alpha)$.

The systemic risk of the bank i is then defined as the difference between the CoVaR of the financial system conditional on firm i being in distress and the CoVaR of the financial system conditional on firm i being in its median state:

$$\Delta CoVaR_{it}(\alpha) = CoVaR_t^{m|r_{it}=(VaR_{it}(\alpha))} - CoVaR_t^{m|r_{it}=Median(r_{it})}) \tag{8}$$

Expressed in dollar terms, we weight it with the market capitalization of bank i:

$$\Delta^{\$}CoVaR_{it}(\alpha) = \Delta CoVaR_{it}(\alpha) * size_{it} \tag{9}$$

We perform the same analysis above using the Delta CoVaR measure from Adrian and Brunnermeier. Following their approach, we use the dollar value of the systemic risk measure, defined as $\Delta^{\$}CoVaR_{it}(\alpha) = \Delta CoVaR_{it}(\alpha) * size_{it}$.

11.1.2 MES

The Marginal Expected Shortfall is the firm's expected loss conditional on the market being in its lower tail. It is a market measure of the exposure of each individual firm to shocks to the aggregate system.

First developed theoretically by Acharya et al. (2017), we estimate the dynamic version as Brownlees and Engle (2012). Therefore, we assume a bivariate daily time series model of the equity returns of institution i, dependent on a value-weighted market index m:

$$\begin{aligned} r_{m,t} &= \sigma_{m,t}\varepsilon_{m,t} \\ r_{i,t} &= \sigma_{i,t}(\rho_{i,t}\varepsilon_{m,t} + \sqrt{1-\rho_{i,t}^2}\xi_{i,t}) \end{aligned}$$

We use the MSCI Europe index for the market return $r_{m,t}$ as a representative benchmark for our sample of European banks. The return volatilities of each institution i $\sigma_{i,t}$ and of the market $\sigma_{m,t}$ are estimated by an asymmetric GJR GARCH model (Glosten, Jagananthan and Runkle, 1993). The correlation between each institution return and the European market index $\rho_{i,t}$ is estimated by a Dynamic Conditional Correlation (DCC) model (Engel, 2002).

Then, we identify extreme downturns by falls in the daily market index higher than its 95% VaR. The expected daily loss of the bank returns (MES) is therefore:

$$MES_{it}(c) = E_{t-1}(r_{it}|r_{mt} < c = q_{5\%}) \tag{10}$$

We construct individual MES for each institution separately and calculate the aggregate measure as an equal-weighted average.

11.1.3 SRISK

SRISK is defined as the capital shortfall of an institution in the event of an major aggregate crisis:

$$\begin{aligned} SRISK_{i,t} &= E_{t-1}[Capital\ shortfall_i|Crisis] \\ &= E_{t-1}[k(Debt + Equity) - Equity|Crisis] \end{aligned} \tag{11}$$

where k is the prudential capital ratio, that we assume 8% in our main analysis. As robustness checks, we also conduct the inference analysis using capital ratio of 3% and 5.5%.

Extending from the MES above, we take into account prolonged events of crisis, liabilities and market capitalization of the bank. The Long-Run Marginal Expected Shortfall (LRMES) is the expected loss in equity value of bank i, if the market were to fall by more than the a d threshold within the next six months. Assuming the six-month crisis threshold for the market index decline as d=40%, and beta is the dynamic market beta, we approximate it as:[30]

$$LRMES_{it} = 1 - \exp\left(ln(1-d)beta\right) \tag{12}$$

We assume that in case of major market distress, debt cannot be renegotiated in the short term, therefore outstanding book value of debt does not change while the current equity market value falls the LRMES. The the expected capital shortfall a bank would experience in case of distress is therefore:

$$SRISK_{it} = E_{t-1}[k(Debt_{i,t}) - (1-k)(1 - LRMES_{i,t})Equity_{i,t}] \tag{13}$$

Once the individual $SRISK_{i,t}$ are estimated per each bank, the relative exposure of firm i to the aggregate SRISK of the financial sector is:

$$SRISK\%_{i,t} = \frac{SRISK_{i,t}}{\sum_{j \in J} SRISK_{j,t}},\ \ where\ J = firms\ with\ SRISK > 0 \tag{14}$$

It represents the percentage aggregate capital shortfall that would be experienced by this firm in the event of a crisis, and it allows to identify the most systemic institutions in the sector.

[30] Alternatively, Acharya, Engel and Richardson (2012) suggest to estimate LRMES without simulation from the daily MES, as the equity value loss over a six-month period conditional on a market fall by more than 40% within the next six months: $LRMES = 1 - e^{(-18*MES)}$.

11.1.4 Z-score

The Z-score is a measure of the degree of solvency of an individual bank. It combines information on bank's performance (ROA), leverage (equity-to-assets ratio), and risk (standard deviation of ROA). Higher values of Z-score represents higher degree of solvency, as it represents a distance to default, as number of standard deviations away from the bank's ROA augmented by the Equity-to-Assets ratio.

As Fiordelisi and Ibanez (2013), we estimate a simplified version of Z-score for each institution, as:

$$Z - score_{it} = \frac{ROA_{it} + E_{it}/TA_{it}}{\sigma_{ROA_i}} \tag{15}$$

11.2 Statistics

Table 4: Large Sample Statistics

Sector	SRISK				Beta	ΔCoVaR	MV
	< 1996	1996-2006	2006-2008	> 2008			
Banks	2280.471	2890.016	7079.194	11388.29	.7360346	.0074475	7817.312
Diversified	727.5312	420.9213	1044.786	1904.564	.6127794	.0068244	1792.487
Insurers	-547.8529	1906.837	4677.732	5647.29	.8018688	.0086705	8925.343
Real Estates	-394.7499	-517.7924	-876.4478	-287.987	.5446723	.0047947	1121.411

[a] This table reports the summary statistics of the financial institutions in our whole sample. by financial subsector, we report average SRISK% (in the four subperiods of interest), market Beta, Delta CoVaR and market capitalization.

Table 5: Small Sample Statistics

Name	Country	SRISK				Beta	ΔCoVaR	MV
		< 1996	1996-2006	2006-2008	> 2008			
Bank Fuer Kaernten Und Steiermark	AUT	14.22134	-59.75613	-46.33916	43.12871	.2143777	.0065933	486.8625
Bank Fuer Tirol Und Vorarlberg	AUT	14.81701	-32.93632	141.5505	320.8975	.282841	.005198	490.1185
Erste Group Bank	AUT		4639.103	5917.598	10963	1.087557	.0125299	13243.07
Oberbank	AUT	107.6971	279.0604	181.6947	256.8992	.3012121	.0066912	987.3725
Raiffeisen International Bank Holding	AUT		-950.7543	-1573.622	6417.921	1.468486	.0137832	12022.19
Unternehmens Invest	AUT		-51.19232	-51.56719	-51.31037	.3092515	.0029117	82.14931
KBC Group	BEL	2446.67	5421.85	8437.08	15684.56	1.016361	.0096414	19903.96
Bank Coop	CHE	175.2317	164.858	-151.8836	313.4363	.1865398	.0047486	697.6836
Bank Linth LLB	CHE		35.2001	-24.73893	68.91928	.1967701	.0039515	262.3995
Edmond de Rothschild (Suisse)	CHE		-28.87809	-396.6915	257.5472	.3697498	.0064649	778.4694
St.Galler Kantonalbank	CHE		245.5587	-372.9412	309.5656	.3811617	.0099404	1909.731
UBS Group	CHE	8945.425	29101.2	72145.35	52753.51	1.078454	.0136245	56299.92
Valiant Holding	CHE		54.74283	-657.2963	291.9383	.2967349	.0059943	1764.552
Vontobel Holding	CHE	-218.2216	-618.8327	-446.8082	4.905521	.7540862	.0104863	1731.418
Zuger Kantonalbank	CHE	198.8947	72.12868	-109.2551	-155.2904	.2331743	.004816	750.4201
Bank of Cyprus Public Co Limited	CYP		-535.4931	-1486.459	1524.285	.5952032	.0068917	3565.318
Hellenic Bank	CYP		72.59184	-30.18251	421.175	.5971429	.0063062	479.5079
USB Bank	CYP		-7.056847	-.4129192	15.75585	.25283	.0008707	48.87632
Aareal Bank	DEU		2474.119	2387.432	2919.631	1.230744	.012334	1458.186
Adcapital	DEU		-69.72336	-124.8044	-71.45582	.3933429	.0045961	156.3118
Allerthal-Werke	DEU		-6.4114	-10.55832	-10.79959	.2690846	.0034523	12.72925
Baader Bank	DEU		-121.6808	-108.3948	-41.39077	.907278	.0078801	228.4999
Bayerische Hypo- Und Vereinsbank	DEU	6729.773	28506.13	13442.02	10060.16	.748991	.0067074	27546.18
Berlin-Hannoversche Hypothekenbank	DEU		2461.578	1056.194	1872.675	.2635079	.0023275	1901.139
Berliner Effektengesellschaft	DEU		-165.7096	-66.82896	-60.9642	.5656877	.0052909	175.7353
C.J.Vogel AG Fuer Beteiligungen	DEU	-49.96786	-71.97611	-74.48666	-117.618	.291241	.0007484	128.2511
Cash.life	DEU		-97.87551	-69.46162	3.133747	.594883	.0016734	142.0449
Comdirect Bank	DEU		-458.8782	-189.1062	253.5582	1.023382	.0106205	1525.255
Commerzbank	DEU	6696.523	22928.54	39000.36	48154.37	1.256342	.0109968	13713.74
DVB Bank	DEU		423.7643	65.28961	758.4427	.2986232	.0056905	841.345
Dab Bank	DEU		-199.127	-15.37433	103.1377	.9586043	.0074795	640.6317
Deutsche Balaton Aktiengesellschaft	DEU		-68.63236	-76.548	-79.75017	.5070966	.0049941	139.02
Deutsche Bank	DEU	8547.679	41662.42	104853.8	133273.4	1.278272	.0129767	40618.15
Deutsche Beteiligungs	DEU	-28.99577	-146.0597	-183.7969	-174.2623	.726984	.009179	271.7828
Deutsche Boerse	DEU		-2692.741	-1771.02	10573.49	.9898442	.0145578	14595.99
Deutsche Effecten & Wechsel	DEU	-238.4844	-179.8211	-25.62209	-16.26192	.4095766	.0043568	174.8968
Dresdner Bank	DEU	7902.26	17869.69			.9917994	.0075181	14734.96
Euwax AG	DEU		-76.24123	-167.4498	-234.5873	.4110111	.0057634	278.3155
Greenwich Beteiligungen	DEU		-4.318142	-6.369004	-3.948963	.2740479	.0026623	8.175117
Grenke	DEU		-174.6113	-182.9152	-530.8815	.7963759	.0094718	754.023
HSBC Trinkaus & Burkhardt	DEU		-801.3498	-693.9661	-219.7322	.346467	.0038639	2524.88
Heidelberger Beteiligungsholding	DEU		-44.8445	-16.04624	-13.45492	.3052562	.0014765	29.86555
IKB Deutsche Industriebank	DEU	595.7852	1390.092	3008.386	2020.156	.7378272	.0041683	1357.097
ING BHF-Bank	DEU	825.2952	1312.058			.6204178	.0053418	2326.243
KST Beteiligungs	DEU		-21.33921	-27.09604	-6.682449	.5044104	.0062016	36.81924
Kali-Chemie	DEU		-786.9916	-811.3713	-449.1126	.1865147	-.0002971	1014.859
MLP	DEU		-1308.865	-750.0582	-302.7297	.8290849	.0071374	1288.598
Mistral Media	DEU		-28.38215	-16.30481	-1.618629	.4273933	.0033758	25.30354
Mpc Muenchmeyer Petersen Capital	DEU		-227.8456	-344.7596	-36.41208	.7924116	.0067718	455.1406
Oldenburgische Landesbank	DEU		-539.2755	-271.5159	492.8164	.2508443	.0041538	1279.855
Peh Wertpapier	DEU		-22.0874	-43.38097	-28.75606	.5145887	.0054311	59.19286
RM Rheiner Mgmt	DEU		-1.992213	-5.685099	-3.806445	.2816036	.0020169	6.381972
Schnigge Wertpapierh.	DEU		-7.752105	-8.976514	-6.852736	.802636	.0019292	15.29016
Sparta.	DEU		-16.60778	-11.63445	-31.43882	.7058983	.0035152	34.91
U.C.A..	DEU		-49.74316	-21.48834	-5.995719	.5221826	.0050043	43.00204
Value Management & Research	DEU		-16.08503	-22.89594	-4.615294	.4677733	.0020844	26.37955
Vereins- Und Westbank.	DEU	369.938	383.6347			.4374557	.003478	1186.686
mwb fairtrade Wertpapierh.	DEU		-12.85357	-16.18547	-7.82211	.6310511	.0052266	24.16495
Banco De SAbadell	ESP		-350.9346	138.2247	7087.081	.8638371	.011291	8535.663
Banco Popular Espanol.	ESP	-166.9554	-2303.011	-1191.385	7613.467	.9713836	.0104589	10354.23
Banco Santander	ESP	1061.09	6811.238	22332.05	61398.66	1.159763	.0135965	61993.45
Bankinter.	ESP	8.397855	84.79258	1352.359	2403.317	1.020771	.0110242	3703.003
Credit Industriel Et Commercial	FRA		8132.779	12142.85	15087.85	.403918	.0092354	7577.139
CRCAM Centre Loire	FRA		430.7095	606.6389	819.0302	.1937384	.0012693	115.0459
CRCAM De Normandie Seine	FRA		439.3432	490.913	754.7281	.3618958	.0080081	114.9045
CRCAM De La Loire-Haute	FRA		277.6884	414.1352	614.9683	.2660342	.0057979	65.28481
CRCAM De La Touraine Et Du Poitou	FRA		309.5782	461.2311	674.665	.2966325	.0069781	98.0285
CRCAM Sud Rhone Alpes	FRA		479.8578	599.6129	950.4944	.3095156	.0066899	128.097
Compagnie De Financement Foncier	FRA	3055.729	3103.208			.6378412	.0031951	1297.015
Natixis	FRA	1045.217	6121.349	27366.57	34619.48	1.036197	.009896	10347.47
Societe Generale Group	FRA	10748.98	26454.56	55677.48	83356.53	1.338951	.0123765	34903.11
Arbuthnot Banking Group	GBR	-50.64982	-49.93948	-40.66502	-21.64422	.3672112	.0045149	125.9428
Barclays	GBR	9082.476	20830.12	99186.35	118115.8	1.261973	.0115427	46398.81
Close Brothers Group	GBR	-106.7236	-736.9025	-538.2259	-499.9091	.7713308	.009164	1641.322
Lloyds Banking Group	GBR	1178.638	-771.1953	15965.05	57274.5	1.136583	.0104569	43142.57
National Westminster Bank	GBR	8486.962	7116.575			1.107512	.0069997	18878.66
Santander UK	GBR	3072.288	9902.597			.9693451	.0080595	13253.14
Standard Chartered	GBR	1679.307	-44.88692	1603.6	16096.51	1.175097	.0108749	26860.11
Alpha Bank	GRC		-1033.565	-1553.479	3291.017	.9137462	.006317	5614.999
Attica Bank	GRC		-84.15314	-29.28466	198.1517	.910203	.004848	445.1873
Eurobank Ergasias	GRC		-1859.822	-2140.136	4799.101	1.02484	.0059927	7975.478
National Bank of Greece	GRC	1451.062	-211.0251	-3937.022	5777.132	.9803826	.0070634	9900.895
Piraeus Bank	GRC		-302.4399	-1281.319	4040.998	1.104049	.0064252	5138.382
Allied Irish Banks	IRL	609.0481	-673.1892	5118.931	-5464.812	1.047109	.0055791	16650.03
permanent tsb Group Holdings	IRL		283.8755	3401.602	3421.3	.927671	.0050396	2716.178
Banca Carige	ITA		-567.0531	-893.8699	1857.153	.7505962	.0095197	3560.437
Banca Finnat Euramerica	ITA	-7.016263	-51.33689	-192.2224	-39.21368	.6551871	.0060871	205.9743
Banca Mediolanum	ITA		-2043.448	-224.8292	1160.893	1.278085	.0128272	4921.9
Banca Monte Dei Paschi Di Siena	ITA		4663.851	6330.839	14045.51	1.110277	.009073	9554.885
Banca Popolare Di Spoleto	ITA		22.81744	26.01397	175.5701	.4906583	.0069308	187.3839
Banco Di Desio E Della Brianza	ITA		-42.62405	26.17808	470.1185	.6959628	.0091319	730.8828
Bper Banca	ITA		375.9536	504.1497	3331.753	.6614867	.0075182	2868.38
Credito Valtellinese Scarl.	ITA		297.1067	339.6009	1544.763	.6673743	.0083212	886.1056
Mediobanca	ITA	-849.5527	-1892.105	-3492.968	2496.675	1.099595	.010301	8941.688
Unicredit	ITA	3197.653	3316.829	31622.27	58034.22	1.143645	.0111054	38805.31
Unione Di Banche Italiane	ITA		1571.623	802.2977	7131.468	1.052218	.0114269	8758.752
Van Lanschot NV	NLD		[illegible]581.521	654.1196	822.1409	.4807536	.00918	1069.654

[a] This table reports the list of banks with internal models information. We report country, average SRISK (in the four subperiods of interest), market Beta, Delta CoVaR and Market capitalization of each bank.

11.3 Cross-Sectional Trajectories

11.3.1 MES

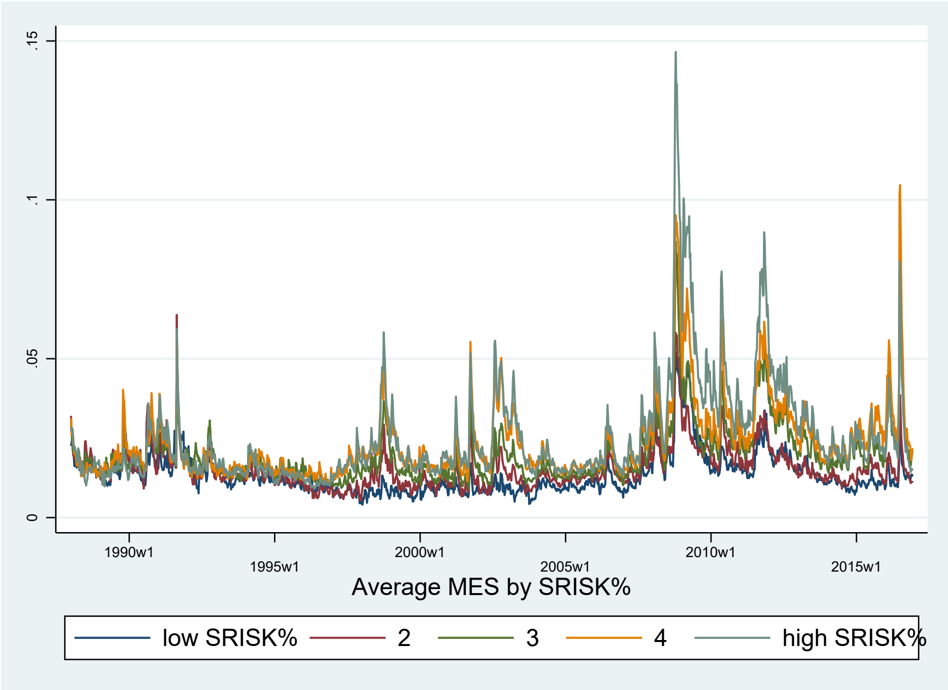

Figure 13: Evolution of exposure to systemic risk - marginal expected shortfall (MES) according to risk group sorted by SRISK.

11.3.2 Delta CoVaR

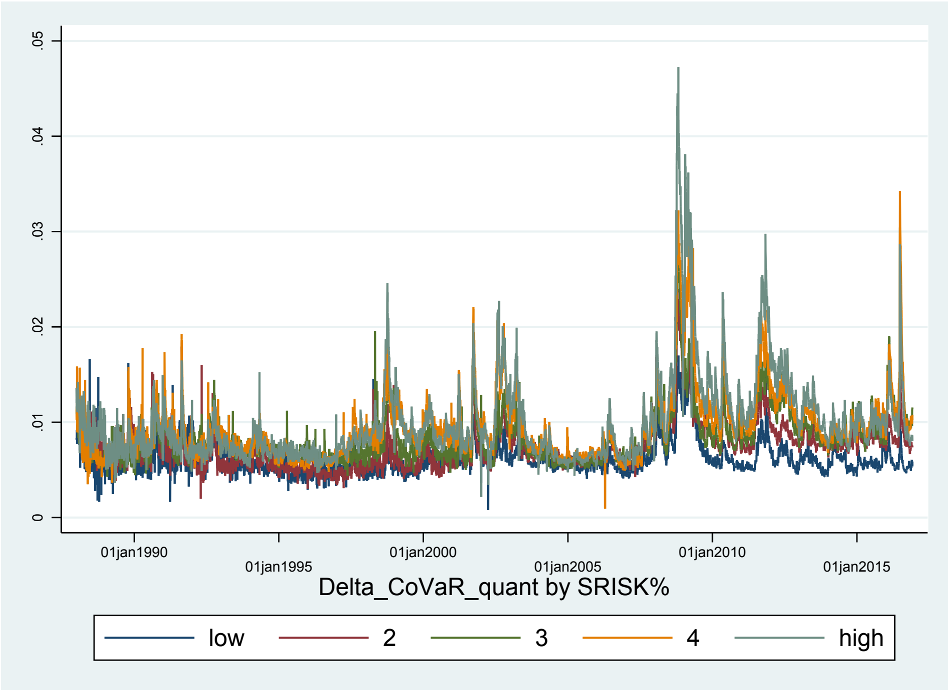

Figure 14: Quantile effects and non-linearities. The Figure reports the evolution of the daily estimated Delta CoVaR (Equation 8) according to risk group sorted by SRISK%, as in Equation 14. The top quintile (gr5) correspond to the group of banks with the highest level of CoVaR, while the bottom quintile (gr1) correspond to the group of banks with the lowest level.

11.3.3 Z-score

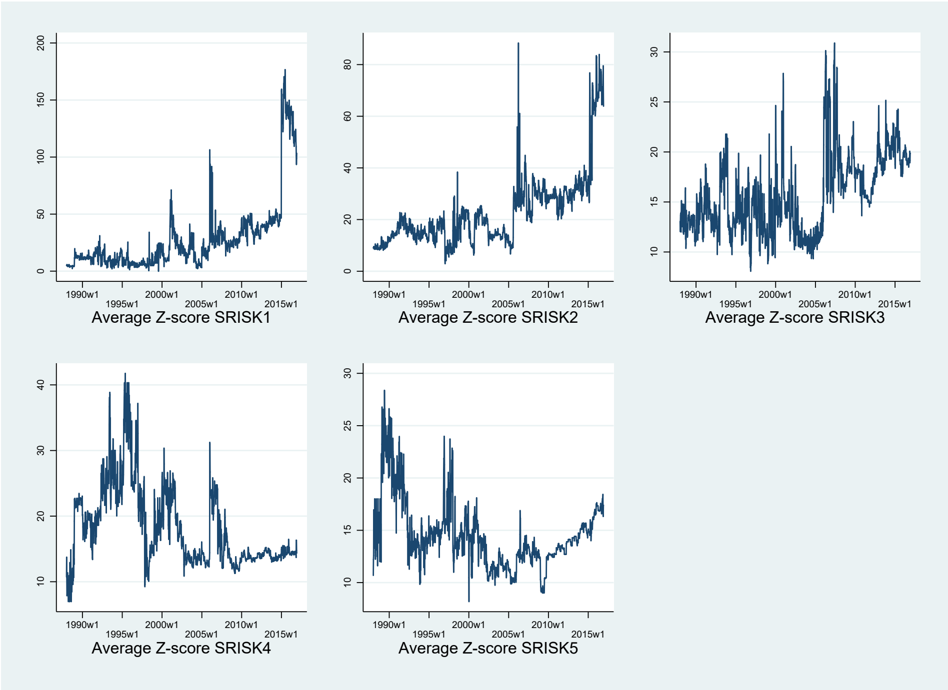

Figure 15: Evolution of idiosyncratic bank risk according to risk group. The Figure reports the evolution of the zscore according to risk group sorted by SRISK%.

11.4 Quantile Regression Delta CoVaR

Table 6: Weekly Unconditional Quantile Regressions of Delta CoVaR

	(1) Q.25	(2) Q.50	(3) Q.75
L.Beta	0.00232***	0.00398***	0.00724***
	(3.71e-05)	(4.69e-05)	(7.13e-05)
L.Zscore	9.19e-06***	-6.24e-06***	-5.93e-06***
	(4.09e-07)	(7.43e-07)	(5.34e-07)
L.CISS	0.00299***	0.00786***	0.0172***
	(0.000176)	(0.000191)	(0.000303)
L.market index	-0.00967***	-0.0201***	-0.0514***
	(0.00251)	(0.00276)	(0.00449)
L.LT interest rate	0.0337***	0.0441***	0.0424***
	(0.00121)	(0.00150)	(0.00241)
MtB	-1.14e-06	8.15e-06***	1.19e-05***
	(2.57e-06)	(1.32e-06)	(4.09e-06)
ln(MV)	0.000491***	0.000737***	0.000393***
	(1.22e-05)	(1.34e-05)	(2.02e-05)
IRBA1	-0.00182***	-0.000374**	-0.00251***
	(0.000160)	(0.000158)	(0.000228)
IRBA2	0.000916***	0.00135***	-0.000279
	(0.000330)	(0.000424)	(0.000515)
IRBA3	0.00379***	0.00532***	0.00157***
	(0.000199)	(0.000265)	(0.000465)
ln(mv)IRBA1	0.000274***	4.70e-06	0.000182***
	(1.71e-05)	(1.73e-05)	(2.68e-05)
ln(mv)IRBA2	-0.000201***	-0.000351***	-0.000219***
	(3.66e-05)	(5.35e-05)	(6.74e-05)
ln(mv)IRBA3	-0.000441***	-0.000553***	-0.000183***
	(1.82e-05)	(2.67e-05)	(5.07e-05)
Market Risk Amendment	0.000933***	-1.31e-05	-0.000222
	(0.000139)	(0.000289)	(0.000299)
Constant	-0.00533***	-0.00693***	-0.00631***
	(0.000194)	(0.000259)	(0.000355)
coun==BEL	0.00118***	-0.00132***	-0.00370***
	(8.60e-05)	(0.000177)	(0.000291)
coun==CYP	0.00101***	-0.00120***	-0.00257***
	(0.000113)	(0.000123)	(0.000168)
coun==DEU	0.000860***	-0.000283***	-0.00153***
	(7.62e-05)	(7.45e-05)	(0.000118)
coun==ESP	0.00144***	0.00159***	0.00223***
	(7.25e-05)	(8.65e-05)	(0.000177)
coun==FRA	0.00123***	0.000815***	-0.00108***
	(8.59e-05)	(9.77e-05)	(0.000156)
coun==GBR	0.00150***	-0.000185**	-0.00220***
	(7.71e-05)	(9.02e-05)	(0.000146)
coun==GRC	-0.00254***	-0.00532***	-0.00846***
	(0.000122)	(0.000116)	(0.000173)
coun==IRL	-0.00367***	-0.00503***	-0.00568***
	(0.000116)	(0.000113)	(0.000172)
coun==ITA	0.00188***	0.000833***	-0.000553***
	(7.48e-05)	(8.72e-05)	(0.000147)
coun==NDL	0.00413***	0.00657***	0.000176
	(7.97e-05)	(0.000105)	(0.000292)
Year Effects	yes	yes	yes
Observations	57,833	57,833	57,833
R-squared	0.372	0.521	0.474
Number of id	87	87	87

[a] This table reports the results from the .25, .50 and .75 unconditional quantile regressions of weekly Delta CoVaR (Adrian and Brunnermeier, 2016). We include the bank-level IRBA dummies (categories 1 to 3) with and without interaction with the market capitalization of the bank, the internal model dummy (from January 1996). We control for country effects, CISS systemic stress, market capitalization, market investment opportunities proxied by the MSCI equity index and short-term interest rate proxy the country policy rates. The standard errors are clustered for banks (Parente et al. 2016).