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# Implied Risk Exposures

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May 21, 2013

## Abstract

Bank risk disclosures, such as Value-at-Risk (VaR), are affected by both changes in market volatility and bank's risk exposures. While the latter is typically unknown to the public, we show how to estimate it from public data on VaR and volatility. We propose a methodology, which we call Factor Implied Risk Exposure (FIRE), that breakdowns a change in risk disclosure into an *exogenous* volatility component and an *endogenous* risk exposure component. In a study of large US and international banks, we show that (1) the main driving force of bank risk disclosures is the shifts in risk exposures, (2) changes in risk exposures are negatively correlated with volatility changes, which suggests that banks reduce risk taking when volatility increases, and that (3) changes in risk exposures are positively correlated among banks, which is consistent with banks exhibiting herding behavior in trading.

*Keywords:* Herding, Risk Disclosure, (Stressed) Value-at-Risk, Regulatory Capital

*JEL Classification:* G21, G28, G32

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# 1 Introduction

Public risk disclosures at banks serve two main purposes. First, they reduce information asymmetry between the bank and its investors/depositors, and hence lower the bank's cost of capital. Second, they are used by banking regulators to set banks' regulatory capital. During economic downturns, as market volatility spikes, risk disclosures and capital requirements tend to mechanically increase. In response, many banks are forced to liquidate part of their trading positions, which further amplifies market volatility (Brunnermeier and Pedersen, 2009; Merrill et al., 2013). The resulting adverse feedback effects are stronger when banks have correlated risk exposures as they tend to sell the same assets at the same time (Morris and Shin, 1999; Persaud, 2000; Farhi and Tirole, 2012).

In this paper, we extract information about the actual risk exposures of banks from their risk disclosures, with special emphasis on Value-at-Risk (VaR).<sup>1</sup> The level of risk disclosures depends on two main factors. First, it reflects current market conditions and as such, tends to rise with market volatility. A second driving force of a bank's risk disclosures, but one that is often hidden to the public eye, is the actual risk exposures of the bank. Indeed, taking over a major stock broker would lead to a higher equity VaR for the acquiring bank. Similarly, implementing an aggressive trading strategy on the commodity market would certainly boost the commodity risk figures.

We show how to decompose a change in risk disclosure into an *exogenous* volatility component and an *endogenous* risk exposure component. The trick we use is straightforward, yet powerful. For a broad family of distributions, the VaR is defined as the product of the standard deviation of the return and the dollar amount invested (up to a constant scaling factor). Consequently, the change in VaR can either be due to a change in volatility or in the amount invested, or both. As the former two pieces of information are public information, they can be used to extract an implied measure of the latter. This framework, which we call Factor Implied Risk Exposure (FIRE), allows us to answer three related research questions. What is the main driving force for banks' risk disclosure: volatility or risk exposures? Do volatility and risk exposure components move in the same direction? If they do, they exacerbate the

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<sup>1</sup>The VaR corresponds to a loss that should only be exceeded with a given target probability over a given time horizon. The perimeter of the VaR model is the trading portfolio of the financial institution.

procyclicality of risk disclosures and, in turn, of banks' regulatory capital. Our third question is: Are changes in risk exposures correlated across banks? In other words, we investigate whether banks exhibit herding behavior in trading and whether herding strengthens when financial markets are under stress.

To develop the intuition underlying our approach, we display in Table 1 the changes in VaR for ten large US and international banks during an episode of substantial reduction in volatility (2008Q4-2009Q4). The VaR figures have been computed by the banks with a 99% confidence level and with a one-day horizon. One attractive feature of this dataset is that it includes risk figures (*factor VaR*) that are defined separately for each source of risk: equity risk, interest rate risk, foreign exchange (FX) risk, and commodity price risk. During this period, volatility fell across all asset classes. The actual reduction in volatility was 46% in the equity market, 43% in the fixed-income market, 39% in the FX market, and 59% in the commodity market.<sup>2</sup> Despite the overall drop in volatility, we identify 17 cases, out of 40, in which the VaR *increased* over the same period. One potential explanation of this puzzling result is that volatility ( $\downarrow$ ) and risk exposures ( $\uparrow$ ) moved in opposite directions and that the risk exposure effect dominated the volatility effect for some banks.

< **Insert Table 1** >

In the empirical part of the paper, we use quarterly VaR data publicly disclosed by the same ten banks between 2007 and 2012. We use separate VaR figures for each major source of risk: equity, interest rate, FX, and commodity. To control for concurrent changes in volatility, we use several proxies including implied volatility and historical volatility. Our empirical analysis leads to several new findings on the risk taking of banks. First, we find that VaR covaries more frequently and more strongly with risk exposures than with market volatility. Second, we show that changes in risk exposures are negatively correlated with volatility changes, which suggests that banks reduce risk taking when volatility increases. Third, changes in risk exposures are positively correlated among banks, which is consistent with banks engaging in herding behavior. When we compare periods of increasing volatility

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<sup>2</sup>We use a specific volatility index for each risk factor (see caption of Table 1 for more details).

and periods of decreasing volatility, we find that the negative relationship between volatility and risk exposures and commonality in risk exposures are present in all market conditions.

Our paper makes several contributions to the literature on financial risk management. First, on the methodological side, we show how to extract an implied measure of changes in bank risk exposures from publicly available data on VaR and volatility. By doing so, we complement Taylor (2005) who shows how to generate volatility forecasts from market risk disclosures. Second, we empirically document the presence of commonality in the risk exposures of large banks. Our decomposition of the changes in risk disclosure allows us to *directly* test for similarities in trading positions by looking at bank risk exposures and not at trading profit-and-loss data (Berkowitz, Christoffersen and Pelletier, 2011). In two distinct studies of large US banks, Berkowitz and O'Brien (2002) and Jorion (2006) both report a moderate correlation between US banks' trading profit-and-loss, which does not support the herding hypothesis. Differently, our empirical evidence on the dynamics of bank risk exposures during the recent crisis is consistent with herding in trading. Third, we contribute to the debate on the procyclicality of regulatory capital. We report a negative correlation between market volatility and risk exposures, which suggests that banks reduce risk taking when volatility surges. This contrarian risk taking behavior can be seen as an attempt to dampen the procyclicality of bank regulatory capital. However, as banks tend to rebalance their risk exposures at the same time and in the same direction, this intended reduction in regulatory capital is partly offset by some volatility feedback effects.

The outline of the paper is as follows. In Section 2, we present a methodology allowing us to extract information about changes in banks' risk exposures from public data. Section 3 presents the empirical analysis using actual VaR data for a sample of large US and international banks. We show in Section 4 how to extend the methodology to other types of risk disclosures. Section 5 summarizes and concludes our study.

## 2 Dynamics of Risk Disclosure

### 2.1 FIRE Methodology

When the distribution of the (demeaned) returns belongs to the location-scale family, the conditional VaR of an asset can be expressed as:

$$VaR_t = -\sigma_t F^{-1}(\alpha) W_t \quad (1)$$

where  $\sigma_t$  is the conditional volatility of the asset return,  $F^{-1}(\alpha)$  is the  $\alpha$ -quantile of the standardized return distribution, and  $W$  is the dollar amount invested in the asset (Jorion, 2007). We see that there are two factors driving the VaR in this set-up, namely the volatility and the amount invested.<sup>3</sup> The change in amount invested can be due to the return of the asset or to inflow/outflow from the investor. The change in VaR is given by:

$$\Delta VaR_t = VaR_{t+1} - VaR_t \quad (2)$$

$$= -\sigma_{t+1} F^{-1}(\alpha) W_{t+1} + \sigma_t F^{-1}(\alpha) W_t \quad (3)$$

$$= -F^{-1}(\alpha) (\sigma_{t+1} W_{t+1} - \sigma_t W_t). \quad (4)$$

Note that the coverage rate  $\alpha$  is assumed to be constant between two dates. The percentage change in VaR is:

$$\frac{\Delta VaR_t}{VaR_t} = \frac{-F^{-1}(\alpha) (\sigma_{t+1} W_{t+1} - \sigma_t W_t)}{-\sigma_t F^{-1}(\alpha) W_t} \quad (5)$$

$$1 + \frac{\Delta VaR_t}{VaR_t} = \left(1 + \frac{\Delta \sigma_t}{\sigma_t}\right) \left(1 + \frac{\Delta W_t}{W_t}\right) \quad (6)$$

$$1 + \% \Delta VaR_t = \left(1 + \% \Delta \sigma_t\right) \left(1 + \% \Delta W_t\right). \quad (7)$$

As a result, the percentage change in the dollar amount invested in the asset is:

$$\% \Delta W_t = \frac{1 + \% \Delta VaR_t}{1 + \% \Delta \sigma_t} - 1. \quad (8)$$

This equation is extremely useful. It allows us to infer the change in amount invested (unknown) from the change in VaR and volatility (both being observed).

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<sup>3</sup>The two-dimensional nature of VaR is made clear in Goldman Sachs' latest annual report (2012, page 89): "Even if our inventory positions were unchanged, our VaR would increase with increasing market volatility and vice versa".

Although our methodology is very general, we focus in this paper on the actual risk disclosures of financial institutions. A common practice at large banks is to disclose their VaR for each risk factor, such as equity, interest rate, FX, and commodity (Pérignon and Smith, 2010a; Basel Committee on Banking Supervision, 2011). Specifically, a factor VaR indicates the maximum loss, at the  $1 - \alpha$  confidence level over a given horizon, that can be due to a given source of risk. For each bank  $i$ , we model the bank return on factor  $f$ ,  $R_{ift}$ , as a function of the factor return,  $R_{ft}$ , and an idiosyncratic return,  $\varepsilon_{ift}$ :

$$R_{ift} = \beta_{ift} R_{ft} + \varepsilon_{ift}. \quad (9)$$

For instance, for equity, this means that the return on the bank's equity portfolio can be imperfectly correlated with the US equity market, as proxied by the S&P 500 stock index. The idea behind the one-factor structure is that we focus on a subportfolio that is predominantly affected by one major source of risk (e.g., equity portfolio, commodity portfolio). From Equation (9), we can express the variance of  $R_{ift}$ ,  $\sigma_{ift}^2$ , as:

$$\sigma_{ift}^2 = \beta_{ift}^2 \sigma_{ft}^2 + \sigma_{\varepsilon t}^2 \quad (10)$$

where  $\sigma_{ft}^2$  is the variance of the factor return and  $\sigma_{\varepsilon t}^2$  is the variance of the idiosyncratic return. In that case, Equation (1) becomes:

$$VaR_{ift} = -\sigma_{ift} F_f^{-1}(\alpha) W_{ift} \quad (11)$$

$$= -\sqrt{\beta_{ift}^2 \sigma_{ft}^2 + \sigma_{\varepsilon t}^2} F_f^{-1}(\alpha) W_{ift} \quad (12)$$

$$= -\sigma_{ft} F_f^{-1}(\alpha) E_{ift} \quad (13)$$

where  $E_{ift}$  is the *risk exposure of firm  $i$  with respect to factor  $f$  at time  $t$*  defined by:

$$E_{ift} = W_{ift} \sqrt{\beta_{ift}^2 + \frac{\sigma_{\varepsilon t}^2}{\sigma_{ft}^2}} \quad (14)$$

We notice that when  $\sigma_{\varepsilon t} \ll \sigma_{ft}$ , the risk exposure converges towards  $W_{ift} \beta_{ift}$ . What this expression tells us is that there are two main ways for a bank to modify its risk exposure: first, the bank can change the *size* of its portfolio and second, it can modify the *sensitivity* of its portfolio with respect to a risk factor.

The change in VaR is given by:

$$\Delta VaR_{ift} = -\sigma_{ft+1} F_f^{-1}(\alpha) E_{ift+1} - \sigma_{ft} F_f^{-1}(\alpha) E_{ift} \quad (15)$$

$$= -F_f^{-1}(\alpha) (\sigma_{ft+1} E_{ift+1} - \sigma_{ft} E_{ift}). \quad (16)$$

The percentage change in VaR is:

$$\frac{\Delta VaR_{ift}}{VaR_{ift}} = \frac{-F_f^{-1}(\alpha) (\sigma_{ft+1} E_{ift+1} - \sigma_{ft} E_{ift})}{-\sigma_{ft} F_f^{-1}(\alpha) E_{ift}} \quad (17)$$

$$1 + \frac{\Delta VaR_{ift}}{VaR_{ift}} = \left(1 + \frac{\Delta \sigma_{ft}}{\sigma_{ft}}\right) \left(1 + \frac{\Delta E_t}{E_t}\right) \quad (18)$$

$$1 + \% \Delta VaR_{ift} = \left(1 + \% \Delta \sigma_{ft}\right) \left(1 + \% \Delta E_t\right). \quad (19)$$

The percentage change in risk exposure between dates  $t$  and  $t + 1$ , which we denote  $\% \Delta E_{ift}$ , is given by:

$$\% \Delta E_{ift} = \frac{1 + \% \Delta VaR_{ift}}{1 + \% \Delta \sigma_{ft}} - 1. \quad (20)$$

Equation (20) gives an expression for the changes in risk exposure as a function of the changes in VaR and in the volatility of the risk factor.

It is important to notice that the FIRE methodology works with both long and short positions. For a short position, the VaR is defined by:

$$VaR_{ift} = -\sigma_{ift} F_f^{-1}(1 - \alpha) W_{ift} \quad (21)$$

with  $W_{ift} < 0$  (Giot and Laurent, 2003). In that case, the percentage change is also given by Equation (18) and the percentage change in risk exposure by Equation (20).<sup>4</sup>

In practice, both the VaR and the volatility have to be estimated. The VaR figures disclosed by the banks are issued from their internal risk model which is generally unknown to the public (Pérignon and Smith, 2010b). The volatility of the risk factor can be estimated by a GARCH model, a realized/historical measure, or by an implied volatility measure (e.g.,

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<sup>4</sup>If we further assume that the marginal distribution  $F$  is symmetric, then the VaR becomes  $VaR_{ift} = -\sigma_{ift} F_f^{-1}(\alpha) |W_{ift}|$  for both long and short positions. Under the symmetry assumption, the FIRE methodology is robust to a change in position from a long position to a short position, and vice versa. In that symmetric case, the percentage change in risk exposure is still given by Equation (20). As a result, changing the size of the position from 1000 to 200, or from 1000 to -200, lead to the same the changes in risk exposure. We obtain a similar result if we consider the following changes in position size: (from 200 to 1000 and from 200 to -1000), (from -1000 to -200 and from -1000 to 200), and (from -200 to -1000 and from -200 to 1000).



VIX). In practice, both the VaR and the volatility estimates can be affected by estimation risk or model risk (Escanciano and Olmo, 2010; Gouriéroux and Zakoian, 2013). However, as long as the ratio of the estimated VaR (respectively volatility) and the true VaR (respectively volatility) remains constant between  $t$  and  $t+1$ , these potential estimation errors do not affect the risk exposures produced by the FIRE methodology. Indeed, these exposures only depend on the relative variations of VaR and volatility.

## 2.2 Case Study on Goldman Sachs

In order to check whether the changes in risk exposures produced by the FIRE methodology make economic sense, it would be ideal to compare the *estimated* risk exposure changes to the *actual* risk exposure changes. As the latter are typically unknown to the public, such comparison is hard to make in practice. However, we found one firm for which the comparison is possible. Indeed, Goldman Sachs makes some statements in its quarterly public filings about the recent changes in its trading portfolio. To our knowledge, Goldman Sachs is the only financial institution to make such public announcements in a systematic way over an extended period of time.

To be able to extract the implied risk exposures, we collect quarterly equity VaR figures from all Goldman Sachs 10-Q forms between 2003Q1 and 2012Q3.<sup>5</sup> Furthermore, we control for contemporaneous changes in volatility in the stock market using the VIX index. Figure 1 displays the quarterly values of the equity VaR along with the VIX index (both are average measures over the quarter). Eyeballing the figure shows little covariation between the VaR and the market volatility. In fact, if anything, the correlation is negative.<sup>6</sup> For instance, the sharp increase in volatility between 2007-2008 corresponds to a period of massive reduction in risk disclosure for the firm. The negative relationship between equity VaR and VIX may seem surprising at first sight. Especially if we refer to the abundant literature on tail risk in which the positive relationship between tail risk and volatility is crucial (See for instance the excellent survey by Christoffersen, 2009). The fundamental positive relationship between VaR and volatility is of course true if the risk exposure remains constant through time. However, in

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<sup>5</sup>The VaR figures are one-day 99% VaR averaged over a given quarter. See Section 3 for a sample including more banks and more sources of risk.

<sup>6</sup>We got a similar pattern when we replace the VIX by the standard-deviation of daily returns on the S&P500 stock index using a three-month estimation window.

practice, this condition is violated as trading positions can vary significantly from one quarter to the next.

< **Insert Figure 1** >

For each quarter Q in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1 using the FIRE methodology. We plot the changes in equity VaR, volatility, and risk exposure in Figure 2. We notice that the VaR increased steadily between 2003 and 2007 whereas the volatility decreased over the same period. This preliminary piece of evidence suggests that the VaR is not only driven by the volatility and that changes in risk exposure is likely to play an important role in the dynamics of the risk disclosure. The relationship between the VaR and the market volatility remains negative over the entire sample period. Differently, the changes in VaR and in risk exposures are positively correlated.

< **Insert Figure 2** >

As a cross-validation exercise, we contrast the risk exposure estimates with statements made by the firm about its current equity risk exposure. In each quarterly report, Goldman Sachs complements the VaR figures with information about any substantive changes in its investment strategy over the past year. For instance, in its 10-Q form dated May 2008, Goldman Sachs mentions that "*Our average daily VaR increased to \$184 million for the second quarter of 2008 from \$133 million for the second quarter of 2007. The increase was primarily due to higher levels of volatility [...]. These increases were partially offset by a decrease in exposures to equity prices*". Over this particular period (2008Q2 vs. 2007Q2), the FIRE methodology successfully indicates the direction of the change in risk exposures. It generates a 51% decrease in implied risk exposure for equity while, at the same time, the VIX index increased by 61%.

We conduct a similar analysis for all 27 quarterly reports between 2004Q1 and 2012Q3. For each quarter, we compare the change in equity risk exposure provided by the FIRE

methodology with the information disclosed by the firm in its 10-Q report. As shown in Table 2, we have not been able to find any case in which the FIRE estimate and the 10-Q form contradict each other. Note that this result is not due to any major trend in risk exposures as increases in risk exposures are as frequent as reductions in risk disclosure in our sample (nine increases and nine decreases). Furthermore, there are another nine quarters for which Goldman Sachs made no particular comments. Interestingly, we notice that these quarters correspond to periods during which the equity risk exposure was more stable. We find that during high VaR change quarters ( $|\Delta VaR/VaR| > 30\%$ ), the firm makes comments in 92.9% of the cases (13 out of 14 quarters), whereas during low VaR change quarters ( $|\Delta VaR/VaR| \leq 30\%$ ), the firm makes comments in only 38.5% of the cases (5 out of 13 quarters).

< **Insert Table 2** >

We consider a series of robustness checks. First, we replace average VaR and VIX values by their end-of-quarter values. We, again, systematically compare the estimated change in risk exposure given by the FIRE methodology to actual statements made by the firm for the 27 different quarters. Second, we conduct a similar analysis using annual 10-K forms between 2004 and 2012, which leads to another 18 comparisons. In annual reports, the company compares its average (respectively year-end) equity-risk exposure in year Y to its average (respectively year-end) equity-risk exposure in year Y-1. For these 45 comparisons, there are specific comments from the firm in 24 cases. In two cases only the sign of the change in implied risk exposure does not match the company's report. However, in both cases, the implied changes in risk exposure is small (-2% and 7%), which makes misclassification more likely.

Overall, the results in this case study are reassuring. Despite the assumptions we made about the distribution and the factor structure of the return, the FIRE methodology seems to produce some risk estimates that fit well with reality. In the following section, we expand the analysis to more banks and factors and investigate the comovements in risk exposures *across* banks.

### 3 Changes in Risk Exposures at Large Banks

#### 3.1 First Input: VaR

In this section, we study the actual changes in risk exposures at large banks before, during, and after the 2008 crisis. These risk exposure changes are extracted from the VaR of ten large US and international banks between 2007Q3 and 2012Q3 (see Table 1 for a list of the sample banks). VaR figures are publically disclosed in the quarterly and annual reports of the firms. These reports have been retrieved from the EDGAR database for US banks and from the firms' websites for international banks. The VaR figures typically have a one-day horizon and a 99% confidence level and are available on four different risk factors: equity, interest rate, FX, and commodity.<sup>7</sup>

We first show in Figure 3 and Table 3 that the factor VaRs exhibit some weak positive covariation across banks. Figure 3 displays the Value-at-Risk of four sample banks (Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank). We notice in this graph that the evolution of the VaR is quite erratic, with large changes from one quarter to the next. It is indeed not uncommon to see a VaR changing by a factor of 3 or 5 within a given year. For some risk types, there is a common trend over the sample period. For instance, the interest-rate VaR of all banks increased over 2007-08 and decreased afterwards. Similarly, there is a clear negative trend for equity risk starting at the end of 2008. Differently, there is much less comovement in the FX and commodity VaRs for these banks. We extend the analysis to all sample banks in Table 3 and report the average correlation between the change in the VaR of a bank,  $\Delta VaR_{ift}$ , and the change in the VaR of all other sample banks for each risk factor,  $\Delta VaR_{jft}$ ,  $j \neq i$  (upper panel). We report a positive average correlation for all four risk factors, which reflects the fact that VaR numbers are affected by some common volatility shocks. However, the magnitude of these correlations is not very high: in the 30%-40% range for equity and interest rate and less than 10% for FX and commodity. Furthermore, we measure in the lower panel of Table 3 the frequency with which the VaRs of banks  $i$  and  $j$  move in the same direction. The percentage of matching signs between  $\Delta VaR_{ift}$  and  $\Delta VaR_{jft}$  is rather low, around 50%,

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<sup>7</sup>Our starting sample was the largest 25 banks in the world according to their total assets as of June 2012. We then selected all banks disclosing end-of-quarter or average VaR for the four main risk factors (equity, interest rate, foreign exchange, and commodity). Then, we selected the longest possible sample period allowing us to get a balanced panel. See the Appendix for more details about the VaR figures.

with a maximum rate of 58% for the interest-rate risk.

< **Insert Figure 3 and Table 3** >

### 3.2 Second Input: Volatility

In order to control for concurrent changes in volatility, we use some *factor volatility indices*. These indices are extracted from options written on the different underlying factors and with maturities between one and three months. Specifically, we use the CBOE VIX index to proxy the volatility of the equity market. The volatility on the fixed income market is measured by the Merrill Lynch Move index, which tracks the implied volatility of Treasury bond prices. The volatility on the FX market is measured by the CVIX, a measure of implied volatility of major currency exchange rates. Finally, the volatility on the commodity market is measured by the OVX, a measure of implied volatility in West Texas Intermediate crude oil prices.<sup>8</sup> We display the evolution of the volatility of each risk factor in Figure 4. As expected, there is strong commonality in the volatility of these risk factors, with spikes after the Lehman collapse in October 2008 and the European sovereign-debt crisis during the summer 2011.

< **Insert Figure 4** >

We show in Table 4 that the VaR and the factor volatility tend to be positively correlated for all risk factors. The average correlation is lowest for commodity risk (2%) and highest for interest rate (48%). We also notice that this correlation is not positive for all banks. In fact, there are only two banks in our sample for which the correlation is positive for all four factors, and the factor VaR of Morgan Stanley is negatively correlated with volatility for all factors. Also, when we compute the percentage of matching signs between the changes in VaR and in volatility, we find a frequency in the 40-50% range. This finding suggests that in many occasions, the evolution of the bank risk disclosures and market volatility diverge. Another implications of our preliminary set of results is that market volatility does not seem to be a dominant driving force for factor VaR.

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<sup>8</sup>We use the same volatility indices as in the Risk (2010) annual VaR survey. We obtain daily data on the factor volatility indices from Bloomberg and Datastream.

< Insert Table 4 >

### 3.3 Implied Risk Exposure

To formally gauge the impact of volatility and risk exposure changes on VaR, we implement the FIRE methodology that was presented in Section 2. For each bank/quarter, we plug the percentage change in VaR and the percentage change in volatility into Equation (20) to get the implied risk exposure variation for each risk factor. To get a first look at the results, we superimpose the evolution of the VaR, volatility, and implied risk exposure for equity in Figure 5. The message we obtain is unambiguous: the change in risk exposures is the main driving force for equity VaR.

Another important finding is that changes in risk exposure and volatility tend to move in opposite directions. We analyze the relationship between risk exposure and volatility for all factors and all banks in Table 5. In the upper panel of the table, we find that the percentage changes in risk exposure and volatility are negative for virtually all firms and all factors. On average, this correlation is -56% for equity, -52% for interest rate, -26% for FX, and -57% for commodity. Moreover, as shown in the lower panel of Table 5, rarely do the changes in risk exposure and volatility move in the same direction.

< Insert Figure 5 and Table 5 >

Are risk exposures correlated across banks? To answer this question, we report in the upper panel of Table 6 the average correlation between the changes in risk exposure of a bank,  $\% \Delta E_{ift}$ , and the change in risk exposure of all other sample banks,  $\% \Delta E_{jft}$ ,  $j \neq i$ . The lower panel of this table displays the frequency with which changes in risk exposure of banks  $i$  and  $j$  move in the same direction. The main takeaway from this table is that there is some strong commonality in bank risk exposures, which is consistent with herding in trading. Indeed, 39 out of the 40 average correlation coefficients among the changes in risk exposures are positive. Moreover, risk adjustments at two random sample banks will go in the same direction between 59% and 65% of the time, which is significantly higher than the figures for the VaR in Table 3.

< **Insert Table 6** >

Furthermore, we control for other variables that could also affect banks' risk exposures and estimate the following OLS multivariate regression:

$$\Delta E_{ift} = \delta_0 + \delta_1 \overline{\Delta E_{jft}} + \delta_2 \Delta \sigma_{ft} + \delta_3 R_{ft} + e_{ift} \quad (22)$$

where  $\overline{\Delta E_{jft}}$  is  $\sum_{i \neq j} \Delta E_{jft} / (N - 1)$ ,  $N$  is the number of sample banks, and  $R_{ft}$  denotes the quarterly return of the risk factor. In our tests, we use the following indices for the four risk factors: S&P500 Index (equity), 3-Year Treasury Constant Maturity Rate (interest rate), Trade Weighted U.S. Dollar Index (FX), and Dow Jones Spot Commodity Index (commodity). The data have been retrieved from Datastream and Bloomberg and cover the period 2007Q3-2012Q3. We see in Table 7 that the estimated coefficients associated with other banks' risk exposures ( $\delta_1$ ) is positive and significant for most factors. This result is suggestive of commonality in risk exposures due to similar investment or hedging policies across banks. In contrast with other sources of risk, we find no commonality in FX risk exposures. The estimated coefficients associated with the change in volatility ( $\delta_2$ ) are all negative and statistically significant, which is consistent with the univariate results in Table 5.

< **Insert Table 7** >

Several reasons can explain the commonality in risk exposures documented in Tables 6 and 7. First, banks can rebalance their trading portfolio in a correlated way because of common information or regulatory constraints. Second, the exposure of two banks with respect to a given factor can also increase because the return of this factor was positive over the past quarter. We intend to disentangle the two channels using the following panel regression:

$$\Delta E_{ift} - r_{ft} = \theta_0 + \theta_1 \overline{\Delta E_{jft} - R_{ft}} + \theta_2 \Delta \sigma_{ft} + e_{ift} \quad (23)$$

where  $\overline{\Delta E_{jft} - R_{ft}}$  is  $\sum_{i \neq j} (\Delta E_{jft} - R_{ft}) / (N - 1)$ . In this specification, we systematically remove the return on the factor from the change in risk exposure. Results in the lower panel of Table 7 clearly indicate that commonality in risk exposure is not mainly due to factor

returns. Indeed, the coefficient associated with other banks' changes in risk exposures ( $\theta_1$ ) remains positive and significant for all factors, except FX. We also notice that the strong negative relationship between volatility and risk exposure is preserved ( $\theta_2$ ).

### 3.4 Robustness Checks

In order to test whether our conclusions remain valid in different market conditions, we split the sample into two subperiods. The first one covers 2007Q3-2008Q4 and corresponds to a period of sharp increase in market volatility (see Figure 4). The second subperiod, 2009Q1-2010Q1, corresponds to a period of massive reduction in market volatility. We show in Table 8 that the quarterly average change in factor volatility ranges between 22% and 27% in the first period and between -11% and -19% in the second period. Overall, we find that our conclusions about the dynamics of the risk exposures are persistent through the different phases of the volatility cycle. In particular, we find that the negative correlation between changes in volatility and risk exposure is a robust feature of the data. Furthermore, we report evidence of commonality in risk exposures across banks in both volatility regimes.

Another robustness check is to change the volatility proxy and rerun the main tests of our analysis. Instead of using volatility indices, we compute a measure of historical volatility during a given quarter. Specifically, we compute the historical standard deviation of the same factor indices as in Table 7 and display this new set of results in Table 9. Overall, our message is preserved. Indeed, we find that VaR covaries much more with risk exposure than with volatility and that banks adjust their trading portfolio in a correlated way. Taken as a whole, the results tend to be stronger with historical volatility than with the volatility indices we use in the rest of the study.

< Insert Tables 8 and 9 >

## 4 Extension to Other Types of Risk Disclosures

So far in this study, we have only focused on one type of bank risk disclosure, namely the VaR. We now show how to infer information about risk exposures from other types of banks' risk disclosures. Under Basel III, all financial institutions with material trading activities



must compute both their VaR using recent data and their *stressed* VaR (sVaR) using data from a particularly volatile period (Basel Committee on Banking Supervision, 2011). This measure is intended to replicate a VaR calculation that would be generated on the bank's current portfolio if the relevant market factors were experiencing a period of stress. As an example, for many portfolios, a 12-month period relating to significant losses in 2007/2008 would adequately reflect a period of such stress.

The stressed VaR is an important innovation in financial risk management. The Ernst & Young (2012) survey of financial services risk management reveals that stress testing and stressed VaR have been the top two areas of improvement in 2012: 55% of the respondents identify stressed VaR as the top area of improvement in transparency. Moreover, under Basel III, stressed VaR is included in the computation of the capital requirements for market risk,  $c_t$ :

$$c_t = \max \{VaR_t; m \cdot VaR_{avg}\} + \max \{sVaR_t; m_s \cdot sVaR_{avg}\} \quad (24)$$

where  $m$  and  $m_s$  are two positive multiplicative factors set by the regulators and subject to an absolute minimum of 3, and the *avg* subscript stands for an average computed over sixty business days.

We show in this section that it is possible to use the FIRE methodology with stressed, instead of standard, VaR figures. In fact, it turns out that is much easier to learn about changes in risk exposures from stressed VaRs than it is from standard VaRs. The reason being that changes in stressed VaR are only due to changes in risk exposures, and not to changes in volatility (recall that, with stressed VaR, the volatility is always measured during the same high-volatility period). We make this point formally by defining the stressed VaR as:

$$sVaR_t = -\Sigma F^{-1}(\alpha) E_t \quad (25)$$

where  $\Sigma$  denotes the conditional variance of the return measured over a particularly volatile period. We note that the variance parameter is not changing from one day to the next as it refers to a given high-volatility episode in the past. As a result, the change in stressed VaR

is given by:

$$\Delta sVaR_t = sVaR_{t+1} - sVaR_t \quad (26)$$

$$= -\Sigma F^{-1}(\alpha) E_{t+1} + \Sigma F^{-1}(\alpha) E_t \quad (27)$$

$$= -\Sigma F^{-1}(\alpha) (E_{t+1} - E_t). \quad (28)$$

The percentage change in VaR is:

$$\frac{\Delta sVaR_t}{sVaR_t} = \frac{-\Sigma F^{-1}(\alpha) (E_{t+1} - E_t)}{-\Sigma F^{-1}(\alpha) E_t} \quad (29)$$

$$= \frac{E_{t+1} - E_t}{E_t}. \quad (30)$$

Then, we conclude that:

$$\% \Delta sVaR_t = \% \Delta E_t. \quad (31)$$

This equation shows that changes in stressed VaR only reflect changes in risk exposures. Unlike with standard VaR, changes in stressed VaR are completely immunized from volatility shocks, which greatly simplifies the analysis.

## 5 Conclusion

Market volatility is clearly an important factor when it comes to compute the VaR of a bank. But we show in this paper that it is unlikely to be the most important factor. Using a sample of large US and international banks, we find that the main driving force of bank risk disclosures is the shifts in risk exposures and not market volatility. Furthermore, we show that changes in risk disclosures are negatively correlated with volatility changes, which suggests that banks reduce risk taking when volatility increases. Finally, we provide empirical evidence of commonality in risk exposures across banks, which supports the view that banks exhibit herding behavior in trading.

The results presented in this paper have some important implications for the dynamics of banks' regulatory capital. Indeed, our paper documents two sources of procyclicality in bank capital. The first one is due to the original increase in volatility while the second one arises from further volatility increases triggered by correlated risk exposures across banks.

The FIRE methodology can be used to reverse engineer the VaR figures of financial institutions. The implied risk exposures could be used to study the empirical performance of the trading strategies of large banks, in the spirit of the study of Agarwal et al. (2013) on hedge funds. One could also test whether some financial institutions lead their peers in terms of investment behavior.

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**Table 1: Change in Factor VaR and Factor Volatility between 2008 and 2009**

| $\% \Delta VaR$        | Equity     | Interest Rate | Foreign Exchange | Commodity  |
|------------------------|------------|---------------|------------------|------------|
| Bank of America        | <b>54</b>  | <b>137</b>    | <b>355</b>       | <b>442</b> |
| BNP Paribas            | -30        | -35           | -48              | <b>25</b>  |
| Citigroup              | -18        | -40           | -62              | <b>20</b>  |
| Credit Agricole        | -56        | -73           | -57              | <b>200</b> |
| Credit Suisse          | <b>33</b>  | <b>36</b>     | -56              | <b>17</b>  |
| Deutsche Bank          | <b>7</b>   | -15           | -37              | <b>10</b>  |
| Goldman Sachs          | <b>161</b> | -46           | -42              | 0          |
| JP Morgan              | -7         | -51           | -74              | -12        |
| Morgan Stanley         | 0          | <b>45</b>     | <b>86</b>        | <b>4</b>   |
| UBS                    | <b>11</b>  | -26           | -56              | -40        |
| $\% \Delta Volatility$ | -46        | -43           | -39              | -59        |

Notes: The source for the VaR figures are the EDGAR database for US banks and firms' websites for international banks. We use a specific implied volatility index for each risk factor. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices. Bold figures denote positive percentage changes. All sample banks report end-of-quarter daily VaR except Bank of America and BNP Paribas that report average daily VaR for each quarter. Values are expressed in percentage points.

**Table 2: Changes in Equity Risk Exposure for Goldman Sachs**

| End of Quarter: | $\% \Delta VaR_t$ | $\% \Delta VIX_t$ | $\% \Delta E_t$ | Excerpts taken from 10-Q forms   |
|-----------------|-------------------|-------------------|-----------------|--|
| 2012Q3          | -13               | -47               | 65              | [n/a]  |
| 2012Q2          | -34               | 15                | -43             | “decreases in the [...] equity prices categories, principally due to reduced exposures”, p.165       |
| 2012Q1          | -41               | -2                | -39             | “decreases in the equity prices [...] categories, principally due to reduced exposures”, p.155       |
| 2011Q3          | -59               | 26                | -67             | “decreases in the equity prices category, principally due to reduced exposures”, p.160               |
| 2011Q2          | -43               | -34               | -13             | “decreases across most risk categories, primarily due to reduced exposures”, p.156                   |
| 2011Q1          | -44               | -8                | -40             | “The decreases in the equity prices [...] categories were primarily due to reduced exposures”, p.138 |
| 2010Q3          | -22               | -5                | -18             | [n/a]  |
| 2010Q2          | 2                 | -20               | 27              | [n/a]  |
| 2010Q1          | 132               | -55               | 417             | “The increase in equity prices was primarily due to increased equity exposures”, p.119               |
| 2009Q3          | 10                | 14                | -3              | [n/a]  |
| 2009Q2          | -24               | 48                | -49             | [n/a]  |
| 2009Q1          | -57               | 85                | -77             | “The decrease in equity prices was primarily due to lower levels of exposures”, p.124                |
| 2008Q3          | -31               | 16                | -41             | “The decrease in equity prices was principally due to position reductions”, p.105                    |
| 2008Q2          | -22               | 61                | -51             | “decrease in exposures to equity prices”, p.101  |
| 2008Q1          | -7                | 120               | -58             | [n/a]  |
| 2007Q3          | 59                | 27                | 25              | “primarily reflecting increased levels of exposure and volatility in [...] equity prices”, p.86      |
| 2007Q2          | 22                | 9                 | 12              | “primarily due to increased levels of exposure to [...] equity prices”, p.85                         |
| 2007Q1          | 39                | -7                | 50              | “primarily due to increased levels of exposure to equity prices”, p.79                               |
| 2006Q3          | 53                | 26                | 21              | [n/a]  |
| 2006Q2          | 219               | -8                | 248             | “The increase was primarily due to higher levels of exposure to equity prices”, p.90                 |
| 2006Q1          | 138               | -5                | 151             | “The increase was primarily due to higher levels of exposure to equity prices”, p.86                 |
| 2005Q3          | 29                | -24               | 71              | “The increase was primarily due to higher levels of exposure to equity prices”, p.79                 |
| 2005Q2          | -30               | -19               | -13             | “The decrease was primarily due to lower levels of exposure to equity prices”, p.75                  |
| 2005Q1          | -22               | -23               | 2               | [n/a]  |
| 2004Q3          | 29                | -19               | 60              | “The increase was primarily due to higher levels of exposure to equity prices”, p.65                 |
| 2004Q2          | 54                | -32               | 126             | “The increase was primarily due to higher levels of exposure to equity prices”, p.65                 |
| 2004Q1          | 19                | -44               | 113             | [n/a]  |

Notes: This table presents the 1-year percentage changes in equity VaR (average daily VaR over the quarter), VIX, and equity risk exposures for Goldman Sachs between 2004Q1 and 2012Q3 (27 quarters). The VaR figures are from the firm’s 10-Q forms, the VIX is from the CBOE website, and the changes in risk exposures are computed using the FIRE methodology. The right column of the table contains excerpts taken from the 10-Q forms of Goldman Sachs. [n/a] indicates that the 10-Q form contains no specific sentences about changes in equity risk exposures. Values are expressed in percentage points.

**Table 3: Correlation in Factor VaR across Banks**

| <b>Average Correlation</b> | Equity    | Interest Rate | Foreign Exchange | Commodity |
|----------------------------|-----------|---------------|------------------|-----------|
| Bank of America            | -29       | 8             | -6               | -17       |
| BNP Paribas                | 43        | 42            | 7                | 21        |
| Credit Agricole            | 50        | 50            | 5                | -18       |
| Credit Suisse              | 48        | 37            | -9               | 23        |
| Citigroup                  | 47        | 34            | 15               | 25        |
| Deutsche Bank              | 52        | 55            | 1                | -22       |
| Goldman Sachs              | 42        | 48            | 18               | 22        |
| JP Morgan                  | 3         | 46            | 16               | 18        |
| Morgan Stanley             | 16        | 16            | -5               | 15        |
| UBS                        | 49        | 3             | 2                | 15        |
| <i>Sample Average</i>      | <i>32</i> | <i>34</i>     | <i>4</i>         | <i>8</i>  |
| <b>% of Matching Signs</b> | Equity    | Interest Rate | Foreign Exchange | Commodity |
| Bank of America            | 38        | 52            | 49               | 48        |
| BNP Paribas                | 47        | 65            | 51               | 40        |
| Credit Agricole            | 42        | 63            | 38               | 26        |
| Credit Suisse              | 45        | 56            | 54               | 48        |
| Citigroup                  | 48        | 53            | 50               | 51        |
| Deutsche Bank              | 49        | 60            | 51               | 43        |
| Goldman Sachs              | 47        | 60            | 62               | 54        |
| JP Morgan                  | 41        | 62            | 57               | 51        |
| Morgan Stanley             | 48        | 53            | 44               | 47        |
| UBS                        | 50        | 53            | 52               | 40        |
| <i>Sample Average</i>      | <i>46</i> | <i>58</i>     | <i>51</i>        | <i>45</i> |

Notes: The upper panel of the table presents the average correlation between the quarterly VaR of a bank and the VaR of all other sample banks for each risk factor between 2007Q3 and 2012Q3 (21 observations). The lower panel reports the frequency with which quarterly VaR of banks  $i$  and  $j$  move in the same direction (+/+ or -/-). For each bank, we compute the percentage of matching signs between the  $\Delta VaR_{ft}$  of that bank and the  $\Delta VaR_{ft}$  of all other sample banks. Values are expressed in percentage points.



**Table 4: Correlation between Factor VaR and Factor Volatility**

| <b>Correlation</b>         | Equity    | Interest Rate | Foreign Exchange | Commodity |
|----------------------------|-----------|---------------|------------------|-----------|
| Bank of America            | 2         | -17           | 1                | -20       |
| BNP Paribas                | 46        | 72            | 51               | -7        |
| Credit Agricole            | 22        | 76            | 40               | -26       |
| Credit Suisse              | 9         | 44            | -13              | 19        |
| Citigroup                  | 36        | 38            | 57               | -3        |
| Deutsche Bank              | 19        | 62            | 37               | -2        |
| Goldman Sachs              | -18       | 75            | 32               | 35        |
| JP Morgan                  | 62        | 66            | 54               | 33        |
| Morgan Stanley             | -43       | -8            | -31              | -36       |
| UBS                        | 11        | 65            | 1                | 0         |
| <i>Sample Average</i>      | <i>14</i> | <i>47</i>     | <i>23</i>        | <i>-1</i> |
| <b>% of Matching Signs</b> | Equity    | Interest Rate | Foreign Exchange | Commodity |
| Bank of America            | 48        | 43            | 38               | 48        |
| BNP Paribas                | 38        | 57            | 52               | 33        |
| Credit Agricole            | 43        | 43            | 43               | 29        |
| Credit Suisse              | 48        | 62            | 57               | 43        |
| Citigroup                  | 71        | 33            | 33               | 57        |
| Deutsche Bank              | 38        | 48            | 52               | 48        |
| Goldman Sachs              | 48        | 71            | 48               | 57        |
| JP Morgan                  | 43        | 67            | 57               | 38        |
| Morgan Stanley             | 33        | 48            | 24               | 52        |
| UBS                        | 43        | 62            | 29               | 38        |
| <i>Sample Average</i>      | <i>45</i> | <i>53</i>     | <i>43</i>        | <i>44</i> |

Notes: The upper panel of this table presents the correlation between a quarterly bank' factor VaR and the factor volatility between 2007Q3 and 2012Q3 (21 observations). The lower panel reports the frequency with which quarterly VaR of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its  $\Delta VaR_{ift}$  and the  $\Delta \sigma_{ft}$ . Values are expressed in percentage points.

**Table 5: Bank Risk Exposures and Volatility**

| <b>Correlation</b>         | Equity     | Interest Rate | Foreign Exchange | Commodity  |
|----------------------------|------------|---------------|------------------|------------|
| Bank of America            | -61        | -56           | -35              | -36        |
| BNP Paribas                | -53        | -31           | -27              | -62        |
| Credit Agricole            | -48        | -52           | 1                | -46        |
| Credit Suisse              | -59        | -63           | -24              | -67        |
| Citigroup                  | -38        | -45           | -13              | -54        |
| Deutsche Bank              | -60        | -76           | -32              | -58        |
| Goldman Sachs              | -69        | -53           | -30              | -45        |
| JP Morgan                  | -23        | -38           | 17               | -79        |
| Morgan Stanley             | -78        | -67           | -75              | -82        |
| UBS                        | -68        | -39           | -40              | -42        |
| <i>Sample Average</i>      | <i>-56</i> | <i>-52</i>    | <i>-26</i>       | <i>-57</i> |
| <b>% of Matching Signs</b> | Equity     | Interest Rate | Foreign Exchange | Commodity  |
| Bank of America            | 10         | 29            | 19               | 24         |
| BNP Paribas                | 29         | 29            | 38               | 24         |
| Credit Agricole            | 29         | 33            | 43               | 19         |
| Credit Suisse              | 24         | 38            | 38               | 19         |
| Citigroup                  | 48         | 19            | 24               | 38         |
| Deutsche Bank              | 19         | 24            | 29               | 29         |
| Goldman Sachs              | 24         | 43            | 19               | 29         |
| JP Morgan                  | 33         | 43            | 48               | 19         |
| Morgan Stanley             | 14         | 24            | 19               | 14         |
| UBS                        | 24         | 24            | 24               | 24         |
| <i>Sample Average</i>      | <i>25</i>  | <i>30</i>     | <i>30</i>        | <i>24</i>  |

Notes: The upper panel of this table presents the correlation between a quarterly bank' factor VaR and the factor volatility between 2007Q3 and 2012Q3 (21 observations). The lower panel reports the frequency with which quarterly risk exposures of a given bank move in the same direction as the factor volatility (+/+ or -/-). For each bank, we compute the percentage of matching signs between its  $\Delta E_{ift}$  and the  $\Delta \sigma_{ft}$ . Values are expressed in percentage points.

**Table 6: Commonality in Bank Risk Exposures**

| <b>Average Correlation</b> | Equity    | Interest Rate | Foreign Exchange | Commodity |
|----------------------------|-----------|---------------|------------------|-----------|
| Bank of America            | 32        | 36            | -4               | 27        |
| BNP Paribas                | 46        | 25            | 7                | 29        |
| Credit Agricole            | 33        | 41            | 4                | 29        |
| Credit Suisse              | 41        | 40            | 16               | 42        |
| Citigroup                  | 17        | 15            | 8                | 41        |
| Deutsche Bank              | 50        | 42            | 9                | 34        |
| Goldman Sachs              | 53        | 36            | 30               | 29        |
| JP Morgan                  | 18        | 34            | 8                | 47        |
| Morgan Stanley             | 53        | 28            | 11               | 39        |
| UBS                        | 52        | 33            | 24               | 27        |
| <i>Sample Average</i>      | <i>39</i> | <i>33</i>     | <i>11</i>        | <i>35</i> |
| <b>% of Matching Signs</b> | Equity    | Interest Rate | Foreign Exchange | Commodity |
| Bank of America            | 65        | 60            | 53               | 66        |
| BNP Paribas                | 70        | 57            | 57               | 59        |
| Credit Agricole            | 61        | 65            | 53               | 63        |
| Credit Suisse              | 67        | 64            | 56               | 70        |
| Citigroup                  | 61        | 64            | 62               | 63        |
| Deutsche Bank              | 71        | 67            | 62               | 61        |
| Goldman Sachs              | 73        | 64            | 69               | 66        |
| JP Morgan                  | 67        | 67            | 54               | 70        |
| Morgan Stanley             | 71        | 67            | 60               | 69        |
| UBS                        | 68        | 65            | 53               | 66        |
| <i>Sample Average</i>      | <i>67</i> | <i>64</i>     | <i>59</i>        | <i>65</i> |

Notes: The upper panel of the table presents the average correlation between the percentage change in risk exposures of a bank,  $\% \Delta E_{ift}$ , and quarterly changes risk exposure of the nine other banks,  $\% \Delta E_{jft}$ ,  $j \neq i$ , between 2007Q3 and 2012Q3 (21 observations). The changes in risk exposures are obtained using the FIRE methodology. The lower panel reports the frequency with which quarterly changes in risk exposure of banks  $i$  and  $j$  move in the same direction (+/+ or -/-). Values are expressed in percentage points.

**Table 7: Panel Regression Analysis of Changes in Risk Exposures**

|                                      | Equity                    | Interest Rate             | Foreign Exchange          | Commodity                 |
|--------------------------------------|---------------------------|---------------------------|---------------------------|---------------------------|
|                                      | $\Delta E_{ift}$          | $\Delta E_{ift}$          | $\Delta E_{ift}$          | $\Delta E_{ift}$          |
| $\overline{\Delta E_{jft}}$          | 0.385**<br>(0.141)        | 0.499***<br>(0.089)       | -0.062<br>(0.089)         | 0.351*<br>(0.191)         |
| $\Delta \sigma_{ift}$                | -0.309***<br>(0.054)      | -0.467***<br>(0.091)      | -0.615**<br>(0.240)       | -0.642***<br>(0.138)      |
| $R_{ft}$                             | 0.665*<br>(0.342)         | -0.002<br>(0.093)         | -0.595<br>(1.377)         | 0.136<br>(0.274)          |
| Constant                             | 0.075***<br>(0.013)       | 0.056***<br>(0.011)       | 0.133***<br>(0.015)       | 0.078***<br>(0.017)       |
| Observations                         | 210                       | 210                       | 210                       | 210                       |
| $R^2$                                | 0.321                     | 0.306                     | 0.062                     | 0.257                     |
|                                      | $\Delta E_{ift} - R_{ft}$ | $\Delta E_{ift} - R_{ft}$ | $\Delta E_{ift} - R_{ft}$ | $\Delta E_{ift} - R_{ft}$ |
| $\overline{\Delta E_{jft} - R_{ft}}$ | 0.396***<br>(0.150)       | 0.894***<br>(0.061)       | -0.038<br>(0.150)         | 0.401**<br>(0.159)        |
| $\Delta \sigma_{ift}$                | -0.305***<br>(0.094)      | -0.257***<br>(0.087)      | -0.708***<br>(0.194)      | -0.468***<br>(0.171)      |
| Constant                             | 0.074*<br>(0.039)         | 0.030<br>(0.028)          | 0.138***<br>(0.042)       | 0.058<br>(0.038)          |
| Observations                         | 210                       | 210                       | 210                       | 210                       |
| $R^2$                                | 0.205                     | 0.540                     | 0.077                     | 0.170                     |

Notes: This table presents the estimated coefficients and standard errors (in parentheses) for several regressions of the changes in risk exposures for the 10 sample banks using an OLS panel regression with bank fixed effects. The dependent variable is the change in risk exposure ( $\Delta E_{ift}$ ) in the top panel and the difference between the change in risk exposure and the return of the risk factors ( $\Delta E_{ift} - r_{ft}$ ) in the lower panel. \*\*\*, \*\*, \* indicate that the coefficient is statistically significant at the 1%, 5% and 10% confidence level, respectively. Each regression is run separately for each factor, with a constant term over an estimation period covering 2007Q3-2012Q3.

**Table 8: Subsample Analysis**

|  | Equity | Interest Rate | Foreign Exchange | Commodity |
|--|--------|---------------|------------------|-----------|
| Episode of Increase in Volatility (2007Q3-2008Q4)  |        |               |                  |           |
| $\% \Delta Volatility$                             | 26     | 23            | 27               | 22        |
| $\% \Delta VaR$                                    | 1      | 26            | 24               | 3         |
| $\% \Delta E$                                      | -15    | 9             | -0.1             | -13       |
| $Corr(\% \Delta E_{ift}, \% \Delta E_{jft})$       | 19     | 28            | 5                | 46        |
| % of Matching Signs                                | 70     | 52            | 70               | 69        |
| Episode of Reduction in Volatility (2009Q1-2010Q1) |        |               |                  |           |
| $\% \Delta Volatility$                             | -15    | -12           | -11              | -18       |
| $\% \Delta VaR$                                    | 10     | -5            | 14               | 13        |
| $\% \Delta E$                                      | 31     | 16            | 30               | 41        |
| $Corr(\% \Delta E_{ift}, \% \Delta E_{jft})$       | 3      | 58            | 24               | 23        |
| % of Matching Signs                                | 49     | 73            | 63               | 62        |

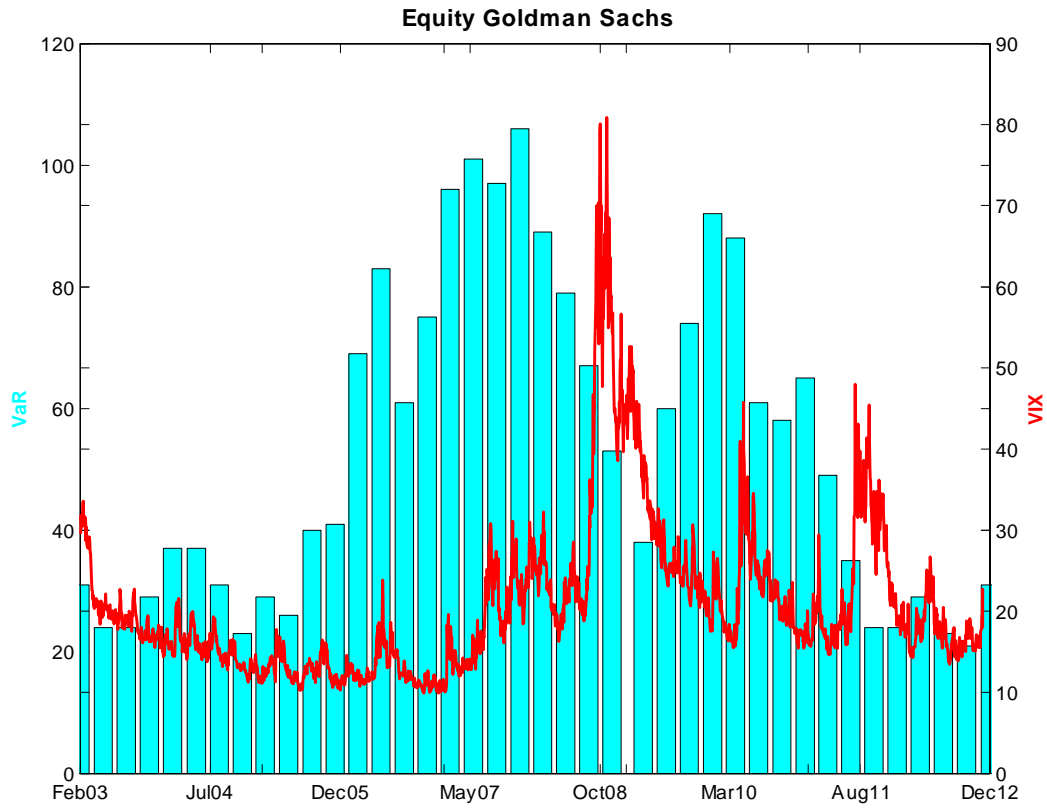
Notes: In this table, we contrast two subsamples. The upper (lower) panel presents the results for an episode of increase (decrease) in market volatility. In each panel, we present the average quarterly percentage change in the factor volatility index ( $\% \Delta Volatility$ ), the average quarterly percentage change in factor VaR ( $\% \Delta VaR$ ), the average quarterly percentage change in risk exposure ( $\% \Delta E$ ), and the average correlation between the percentage change in risk exposures of a bank,  $\% \Delta E_{ift}$ , and quarterly changes risk exposure of the nine other banks,  $\% \Delta E_{jft}$ ,  $j \neq i$ . Values are expressed in percentage points.

**Table 9: Changing the Volatility Proxies**

|   | Equity | Interest Rate | Foreign Exchange | Commodity |
|---|--------|---------------|------------------|-----------|
| Corr( <i>historical</i> $\sigma_{ft}$ ; $\sigma_{ft}$ )                   | 81     | 57            | 84               | 46        |
| Corr( <i>historical</i> $\sigma_{ft}$ ; $\bar{\sigma}_{ft}$ )             | 83     | 65            | 90               | 46        |
| Corr( $VaR_{ift}$ ; <i>historical</i> $\sigma_{ft}$ )                     | 14     | 1             | 20               | 3         |
| % of Matching Signs   | 44     | 47            | 46               | 43        |
| Corr( $\% \Delta E_{ift}$ ; $\% \Delta$ <i>historical</i> $\sigma_{ft}$ ) | -66    | -68           | -40              | -55       |
| % of Matching Signs   | 20     | 17            | 27               | 26        |
| Corr( $\% \Delta E_{ift}$ , $\% \Delta E_{jft}$ )                         | 62     | 55            | 29               | 34        |
| % of Matching Signs   | 74     | 71            | 64               | 64        |

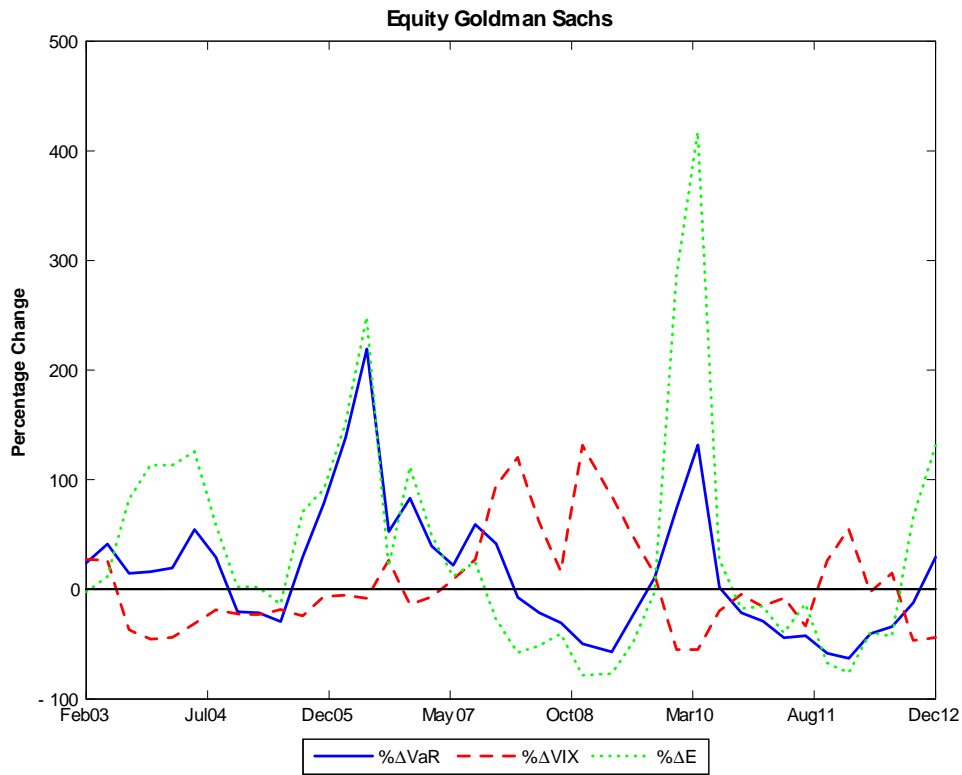
Notes: In this table, we replicate the main results from the FIRE analysis using a different volatility proxy for each risk factor between 2007Q3 and 2012Q3 (21 observations). We compute the historical standard deviation of the S&P500 Index (equity), 3-Year Treasury Constant Maturity Rate (interest rate), Dow Jones Spot Commodity Index (commodity), and Trade Weighted U.S. Dollar Index (FX). Indices are available with a daily frequency and standard deviations are computed using a three-month estimation window. In the first two rows, we compute the correlation between the original implied volatility index (end-of-quarter,  $\sigma_{ft}$ , and average,  $\bar{\sigma}_{ft}$ ) and the historical volatility. The next six rows replicate the results from Tables 4, 5, and 6, respectively. Values are expressed in percentage points.

Figure 1: FIRE Analysis of Goldman Sachs' Equity VaR



Notes: This figure displays the quarterly, average, 99%-confidence level, one-day ahead equity VaR of Goldman Sachs (bars, left axis) and VIX index (line, right axis). The sample period covers 2003Q1-2012Q3 and the VaR figures are in USD millions. Note that the gap in VaR data immediately after November 2008 is due to the fact the company changed its fiscal year-end from November to December.

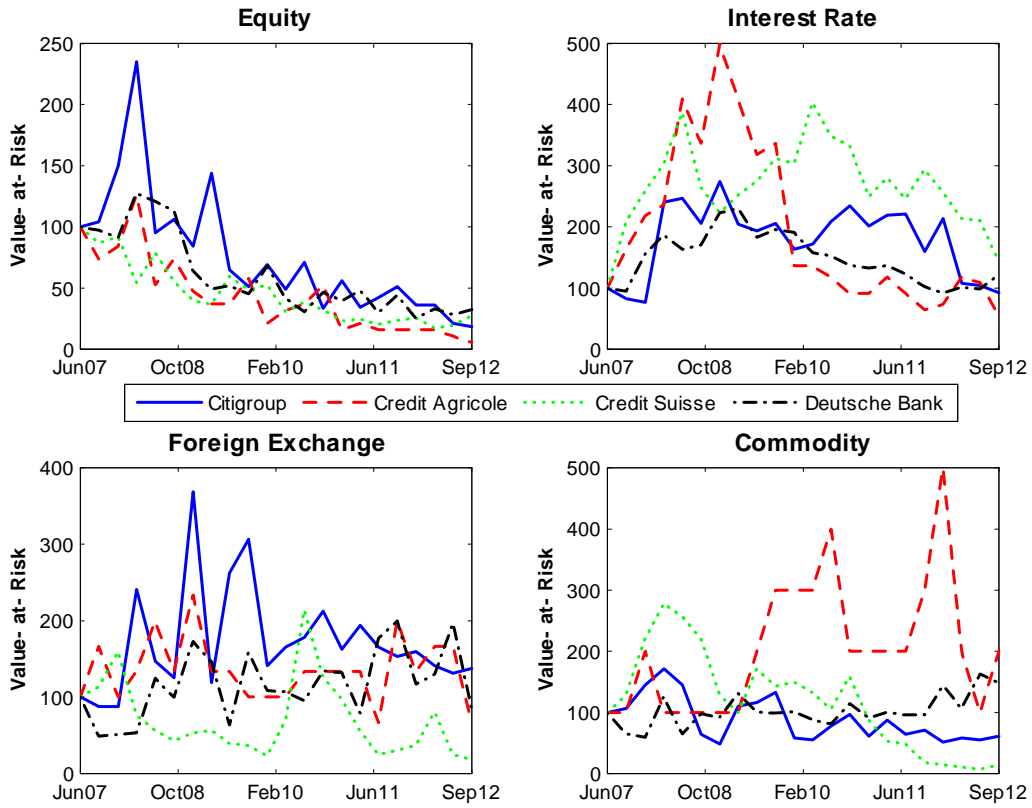
Figure 2: FIRE Analysis of Goldman Sachs' Equity VaR



Notes: This figure displays changes in the quarterly average of the 99% one-day ahead equity VaR (blue solid line), in equity volatility (red dashed line), and in the implied risk exposure (green dotted line) extracted using the FIRE methodology with the VIX index. For quarter Q1-4 in year Y, we extract the change in equity risk exposure between quarter Q in year Y and quarter Q in year Y-1. Results are for Goldman Sachs from 2003Q1 to 2012Q3.

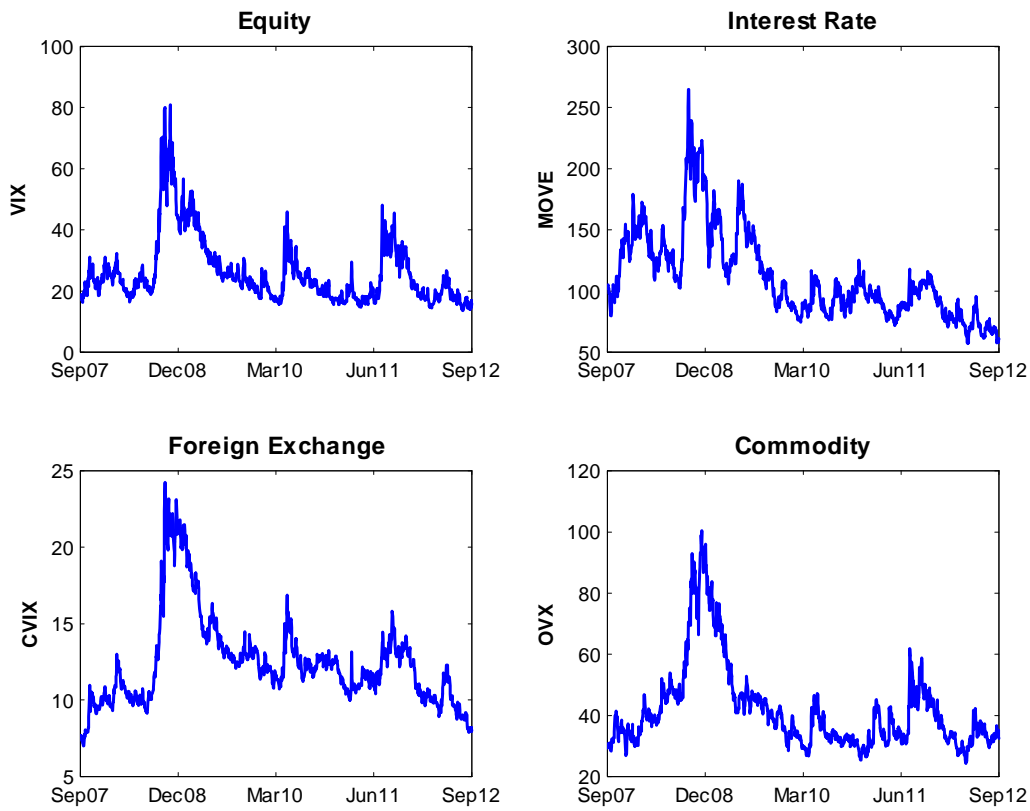


Figure 3: Evolution of the Factor VaR



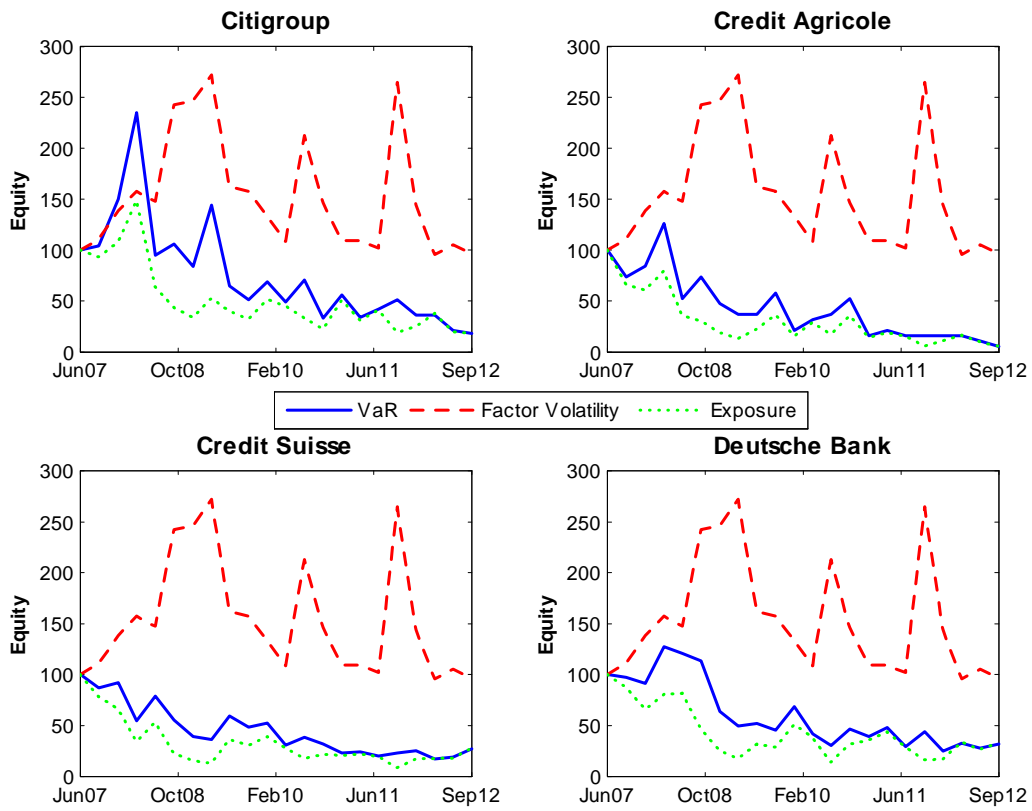
Notes: This figure displays the 99% one-day ahead factor VaR of Citigroup, Credit Agricole, Credit Suisse, and Deutsche Bank for four risk factors (equity, interest rate, foreign exchange, and commodity). All values are set to 100 in 2007Q2.

Figure 4: Evolution of the Factor Volatility Indices



Notes: This figure displays the daily factor volatility for each risk factor (equity, interest rate, foreign exchange, and commodity) from 2007Q2 to 2012Q3. The volatility on the equity market is measured by the Chicago Board Options Exchange VIX index. The volatility on the fixed income market is measured by the Merrill Lynch MOVE index, which tracks the volatility of Treasury bond prices using implied volatility from 30-day options. The volatility on the foreign exchange market is measured by the Deutsche Bank CVIX index, an average 3-month implied volatility for all the major currency pairs. The volatility on the commodity market is measured by the Chicago Board Options Exchange OVX index, a measure of 30-day implied volatility in West Texas Intermediate crude oil prices.

Figure 5: Equity VaR and its Driving Forces



Notes: This figure displays the equity VaR (blue solid line), equity volatility (VIX index, red dashed line), and the implied risk exposure (green dotted line) extracted using the FIRE methodology with factor volatility indices. All values are set to 100 in 2007Q2.

## Appendix: VaR Data

| Bank            | Horizon and Confidence Level  | Type of VaR Disclosed  | Fiscal Year-End                    |
|-----------------|---|--|------------------------------------|
| Bank of America | 1-day VaR 99% from 2007Q2 to 2012Q3   | Average over the quarter   |                                    |
| BNP Paribas     | 1-day VaR 99% from 2007Q2 to 2012Q3   | End-of-Quarter from 2007Q2 to 2008Q1<br>Average over the quarter from 2008Q2 to 2012Q3<br>Both in 2008Q1 |                                    |
| Citigroup       | 1-day VaR 99% from 2007Q2 to 2012Q3   | End-of-Quarter   |                                    |
| Credit Agricole | 1-day VaR 99% from 2007Q2 to 2012Q3   | End-of-Quarter   |                                    |
| Credit Suisse   | 1-day VaR 99% from 2007Q2 to 2012Q3   | End-of-Quarter   |                                    |
| Deutsche Bank   | 1-day VaR 99% from 2007Q2 to 2012Q3   | End-of-Quarter   |                                    |
| Goldman Sachs   | 1-day VaR 99% from 2003Q1 to 2012Q4   | End-of-Quarter<br>Average over the quarter<br>End-of-Year<br>Average over the year                       | November until 2008, then December |
| JP Morgan       | 1-day VaR 99% from 2007Q2 to 2009Q4<br>1-day VaR 95% from 2010Q1 to 2012Q3<br>Both VaR 99% and 95% in 2009                                    | End-of-Quarter   |                                    |
| Morgan Stanley  | 1-day VaR 95% from 2007Q2 to 2012Q3   | End-of-Quarter   | November until 2008, then December |
| UBS             | 10-day VaR 99% from 2007Q2 to 2008Q4<br>1-day VaR 95% from 2009Q1 to 2012Q3<br>Both 10-day VaR 99% and 1-day VaR 95%<br>from 2008Q4 to 2009Q4 | End-of-Quarter   |                                    |