The level and quality of Value-at-Risk disclosure by commercial banks

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\textbf{Abstract}

In this paper we study both the level of Value-at-Risk (VaR) disclosure and the accuracy of the disclosed VaR figures for a sample of US and international commercial banks. To measure the level of VaR disclosures, we develop a VaR Disclosure Index that captures many different facets of market risk disclosure. Using panel data over the period 1996–2005, we find an overall upward trend in the quantity of information released to the public. We also find that Historical Simulation is by far the most popular VaR method. We assess the accuracy of VaR figures by studying the number of VaR exceedances and whether actual daily VaRs contain information about the volatility of subsequent trading revenues. Unlike the level of VaR disclosure, the quality of VaR disclosure shows no sign of improvement over time. We find that VaR computed using Historical Simulation contains very little information about future volatility.

\section{Introduction}

Following a string of high profile trading losses, greater attention has recently been focused on the trading risk faced by commercial banks. In accordance with the 1996 Market Risk Amendment to the Basel Accord (Basel Committee on Banking Supervision, 1996), many bank regulatory agencies have set capital requirements to include a market risk charge that reflects the risk of banks’ trading activities. In the US, banks that are large enough are eligible under the Basel Accord to base their required regulatory capital for market risk on an internal Value-at-Risk (hereafter VaR) model.\footnote{The use of internal VaR to set regulatory capital is not a requirement for US banks.} VaR is defined as the \( p \)th lower tail percentile of trading revenue over the next \( h \) periods \( \hat{R}_{t+h} \), formally \( p = \Pr(\hat{R}_{t+h} < \text{VaR}_{t+h}) \), and has become a standard market risk measure (Jorion, 2006).

In the US, market risk disclosures are required for all public filers that make material use of derivatives (not just banks) under Financial Reporting Release Number 48 (hereafter FRR 48) published by the US Securities and Exchange Commission (1997). VaR disclosure is, along with tabular presentation and sensitivity analysis, one of the three reporting methods described in FRR 48 (Linsmeier and Pearson, 1997).\footnote{Tabular presentation consists of a table of financial instruments (grouped by market risk category and market characteristics) that discloses the fair value of the assets and its future cash-flows. Sensitivity analysis presents the effect on earnings, cash-flows, or fair values of a hypothetical shock on a key risk factor, e.g., a 50 basis-point increase in the short-term interest rate (see Blankley et al. (2000) for an illustration).} A not so well-known consequence of this multi-format disclosure environment is that VaR public disclosures are not mandatory for all 10-K filings as long as an alternative quantitative disclosure format is used.

The first objective of this paper is to study the level of VaR disclosure since the 1996 Market Risk Amendment to the Basel Accord. The fact that both the Basel Accord and FRR 48 encourage \textit{but do not require} VaR-based risk disclosure presents a strong motivation for looking at the actual level of VaR disclosure. It is the very fact that most banks have the option to use VaR that makes their choice empirically interesting. In this paper, we develop an index, labeled the VaR Disclosure Index (hereafter VaRDI), that summarizes the amount of VaR disclosure by banks and the extent to which banks disclose details about VaR construction and provide...
information to facilitate interpretation. Specifically, VaRDI comprises six components: (1) VaR characteristics (holding period and confidence level), (2) summary VaR statistics (high, low, average, year-end VaR, VaR by risk category, and diversification effect), (3) summary information about the previous year’s VaR, (4) histogram or plot of daily VaRs, (5) definition of trading revenues (hypothetical revenues and non-inclusion of trading fees) and histogram or plot of daily trading revenues, and (6) backtesting (number of exceptions, i.e., days when actual trading loss is greater than VaR, and explanations of these exceptions).

We first compute the annual VaRDI for the largest 10 US banks between 1996 and 2005. We find large differences in the level of disclosure across banks and an overall upward trend in the quantity of information released to the public. We then extend the analysis to Canadian banks and show that disclosures in the US are considerably lower than disclosures in Canada. We next consider a cross-section of 60 US, Canadian, and international banks for the year 2005, which allows us to uncover some drastic differences in disclosure across regions: from an overall satisfactory disclosure in Europe and Canada to absolutely no VaR disclosure in China. Interestingly, we find that Historical Simulation is the most popular VaR method in the world, as 73% of banks that disclose their VaR method report using Historical Simulation.

The second objective of this paper is to assess the accuracy of the disclosed VaR figures. Regardless of how much information banks provide about their VaR, disclosure is only useful if the VaR numbers themselves are accurate, i.e., if VaR is “related to actual performance” (Greenspan, 1996). We first check whether the number of VaR exceptions disclosed by the banks corresponds to its expected value, which is 2.5 per year with a 1-day/99% VaR. We detect a pervasive and persistent overstatement of the VaR which leads to too few (often zero) exceptions. These backtesting results suggest that the quality of VaR disclosure has remained low over our sample period. We then study whether actual daily VaRs contain information about the volatility of subsequent trading revenues. To motivate this test recall that VaR is defined as the lower tail percentile of trading revenues and, as a result, will increase with the conditional volatility. In our empirical tests, we use daily data on VaR and trading revenue extracted from publicly available graphs presented in annual reports using a novel data extraction method. We compare the forecasting ability of two volatility measures: the VaR computed by the bank and a forecast from a simple econometric GARCH model. To formally compare these competing estimates, we employ different econometric approaches: (1) an augmented in-sample GARCH model that includes the VaR measure as an additional variable driving the conditional volatility of trading revenues, and (2) an out-of-sample regression of actual volatility on one or both contending volatility measures. Overall, our empirical tests show that VaR (especially when based on Historical Simulation) helps little in forecasting future volatility.

The paper most closely related to ours is Jorion (2002a) who relies on quarterly data released by eight US commercial banks. In particular, he tests whether the VaR on the last day of a given quarter is able to predict the variability of the following quarterly trading revenue. Given the short history and low frequency of VaR reporting, his analysis relies on a small sample for each bank, i.e., between 14 and 23 observations. Out of the eight US banks studied by Jorion (2002a), four displayed a positive and statistically significant relationship between their VaR and actual trading revenue variability. Our analysis differs from Jorion’s (2002a) study since we use higher frequency data, namely daily VaRs and trading revenues, and we estimate a GARCH model as a benchmark against which to compare the VaR forecasts. Furthermore, in our sample period, most banks use Historical Simulation to compute their VaR.

Studying the accuracy of disclosed VaR figures based on proprietary models is important in regard to the debate on banks’ capital requirements. Under the Market Risk Amendment to the Basel Accord (Basel Committee on Banking Supervision, 1996; Hendricks and Hurtle, 1997), the capital charge for market risk can be based on the output of a bank’s internal VaR model rather than on an externally imposed supervisory measure. Many market commentators have indicated that the high degree of autonomy granted to commercial banks in setting capital charges might have some perverse effects. In particular, banks may be inclined to underestimate their VaR in order to reduce their market risk charge (Lucas, 2001) or to decrease the quality of its risk management system (Danielsson et al., 2002). Conversely, in their theoretical analysis of VaR-based capital requirements, Cuoco and Liu (2006) conclude that VaR-based capital requirements can be very effective in inducing truthful revelation of market risk. While many conflicting theoretical models of the accuracy of VaR are available in the literature, little is known on the accuracy of disclosed VaRs. We intend here to contribute to fill this gap.

The rest of the paper is organized as follows. In Section 2, we study the level of VaR disclosure at commercial banks in the US and in the rest of the world. Specifically, we define our Value-at-Risk Disclosure Index and we study its level through time and across banks and countries. Section 3 presents the backtesting results along with the empirical analysis of the relationship between VaR and future volatility. We summarize and conclude our study in Section 4.

2. Level of VaR disclosure

In the US and many other countries, commercial banks are required to provide quantitative information about their trading risks. We undertake an empirical analysis of the actual public disclosure about VaR made by banks to its investors, creditors, and counterparties through financial statements.

2.1. VaR Disclosure Index

To facilitate the empirical analysis we construct a disclosure index, which we label VaRDI. This index aggregates six facets of VaR disclosure into a single number between 0 and 15. The six index components are: VaR characteristics, summary VaR statistics, intertemporal comparison, daily VaR figures, trading revenues, and backtesting. When constructing the index, we give equal weight to all criteria which is of course arbitrary. However, coming up with different weights for each criterion would be even more arbitrary. A maximum of 15 points are allocated if the following pieces of information are publicly released by a given bank:

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3 In an independent study, Hurtle (2007) computes a similar market risk index for a sample of US banks. She finds a positive relationship between public disclosure and subsequent performance of banks.

4 Our sample size is larger than the one used by the Basel Committee on Banking Supervision (2001, 2002, 2003) in its three annual surveys of public disclosures by banks. Moreover, unlike the surveys conducted by the Basel Committee on Banking Supervision, ours is not anonymous.

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5 Hurtle (2003) shows that US banks’ quarterly market risk charges contain valuable information about future risk exposures (see also Liu et al., 2004; Bai et al., 2007; Taylor, 2007; Alexander and Sheedy, 2008).

6 Berkowitz and O’Brien (2002) is the most notable exception.

7 To allay concerns about the arbitrary weights used to construct our index we also constructed a disclosure index using the statistically-based Principal Component Analysis weighting scheme. The equally weighted index we consider is remarkably similar to this statistically-based factor. In particular, the correlation between the first principal component and our proposed VaR Disclosure Index for the 60 banks we consider in 2005 is over 95% (Pearson correlation: 95.25; Spearman correlation: 95.34). This gives us confidence that our results are not driven by our choice of weighting scheme.
1. VaR Characteristics.
   a. Score of 1 if Holding Period (e.g. 1 day, 1 month).
   b. Score of 1 if Confidence Level (e.g. 99%, 95%).

2. Summary VaR Statistics.
   a. Score of 1 if High, Low, or Average VaR.
   b. Score of 1 if Year-End VaR.
   c. Score of 1 if VaR by Risk Category (e.g. Currency, Fixed Income, Equity).
   d. Score of 1 if Diversification Effect is accounted for.

3. Intertemporal Comparison.
   a. Score of 1 if Summary Information about the Previous Year VaR.

   a. Score of 1 if Histogram of Daily VaRs, or score of 2 if Plot of Daily VaRs.

5. Trading Revenues.
   a. Score of 1 if Hypothetical Revenues.
   b. Score of 1 if Revenues without Trading Fees.
   c. Score of 1 if Histogram of Daily Revenues, or score of 2 if Plot of Daily Revenues.

   a. Score of 1 if Number of Exceptions, or score of 2 if Zero Exceptions.
   b. Score of 1 if Explanation of Exceptions.

Besides the basic VaR characteristics (items 1a and 1b), VaRDI rewards the disclosure of both year-end and average values. Although year-end statistics are the most up-to-date information, they are prone to manipulation, i.e., “window dressing”. A bank breaking down its overall VaR across risk categories is awarded one point (item 2c). For instance, one can read in Wachovia 2001 annual report (p. 33) that “average 1-day VaR’s by major risk category and on an aggregate basis are shown in the VAR profile by Risk Type table”. Furthermore, an explicit treatment of the diversification or correlation effect is also valued in the index (item 2d).

Indeed, it is useful to access several estimates of aggregate VaRs that are based on different assumptions about the correlations across assets (e.g. VaR = 10 if we assume zero correlation and VaR = 30 with a correlation of one). The following quotation from JPMorgan Chase 2005 annual report (p. 75) illustrates this point: “JPMorgan Chase’s primary statistical risk measure, VAR, […] provides a consistent cross-business measure of risk profiles and levels of diversification”.

The third component entering into VaRDI aims to signal any change in the level of the exposure to market risk or any meaningful alteration in market risk management (item 3a). As an illustration, the Bank of America 2003 annual report (p. 52) states that “The reduction in average VAR for 2003 was primarily due to the 2002 methodology enhancements and the $5 million decline in real estate/mortgages”.

As for daily VaRs, VaRDI favors time-series of actual daily VaRs (item 4b) over histograms or distributions of daily VaRs (item 4a).

The reason is that histograms remain silent about the dynamics of daily VaRs and do not permit one to assess the persistence or the presence of clusters in VaR figures. Conversely, a perusal of daily VaRs allows us to immediately assess its level and time-series properties. Moreover, if plots of daily VaRs and trading revenues are superimposed, one can easily detect any exceptions or clusters of exceptions.

Information on trading revenues is also central to the construction of the index. Indeed, VaR measures the maximum trading loss that can be faced over a certain horizon and with a given probability, should the trading positions of the bank have remained constant over the investment horizon used to compute the VaR. As a result, in order not to distort the backtesting procedure, one would require hypothetical trading revenues to be disclosed (item 5a), and not actual trading revenues that are affected by intraday adjustments in the bank’s positions. For instance, Royal Bank of Canada 2004 annual report (p. 60) tells investors that “Daily back-testing against hypothetical profit and loss is used to monitor the statistical validity of VAR models”. Also, to be consistent with the definition of VaR, disclosed trading revenues should not be inflated by any fee income and other revenues not attributable to position taking. The ING Bank 2005 annual report (p. 157) states “In addition to using actual results for backtesting, ING also uses hypothetical results, which measures results excluding the effect of intraday trading, fees and commissions”. Consistent with the treatment of daily VaRs, the informational content of a plot of daily trading revenues (and the number of points allocated) is greater than the one of an histogram of trading revenues (item 5c).

The last part of VaRDI concerns the information related to the backtesting procedure. VaRDI confers one point if the number of exceptions is publicly disclosed (item 6a) and another point if the bank explains the reasons that triggered the exceptions (item 6b). In the words of Bank of America (annual report 2001, p. 65); “actual market risk-related losses exceeded VaR measures one day out of 250 total trading days. This occurred immediately following the events of September 11, 2001 due to extreme market conditions” or JPMorgan (annual report 2001, p. 56); “The inset shows that a loss exceeded the VaR on only one day (when the firm recognized trading losses related to its exposure to Enron), a performance consistent with the firm’s VaR’s 99% confidence level”. Finally, in order not to penalize a bank that did not experience any exception over the reported period, we allocate two points when the number of disclosed exceptions is zero (item 5a).

For instance, one can read in the State Street 2005 10-K form (page 59) “For the years ended December 31, 2005, 2004 and 2003, we did not experience any trading losses in excess of our end-of-day value-at-risk estimate”.

It is important to make a clear distinction between our disclosure index and disclosure requirements. US FRR 48 requires all SEC registrants following the VaR disclosing method to publicly report 1a, 1b, 2a or distribution of VaR, and 3a, which corresponds to a VaRDI of four points. VaRDI also goes beyond the Basel II requirements on market risk disclosure (Basel Committee on Banking Supervision, 2006), which requires 1a, 1b, 2a, 2b, 6a, and 6b. An extra piece of information mentioned in FRR 48 and Basel II is the type of VaR model. While we recognize that it is useful to know which VaR proprietary methodology is implemented, we did not explicitly include it as an index component. The reason is that, unlike all the other items in VaRDI, a model description is not a precise item and that banks often make a crude description of their internal VaR estimation engines. We do, however, document the various VaR methods used by bank’s in Section 2.4 below.

8 See Pétrignon and Smith (forthcoming) for an empirical investigation of the diversification among risk-category VaRs at US commercial banks.
9 Note that if both a histogram and a plot of daily VaRs are disclosed at the same time, two points are granted. A similar rule applies to trading revenues (item 5c).

11 Being excessively conservative when setting VaR is more of an issue for backtesting purposes than it is from a disclosure point of view.
12 Note that disclosing year-end VaR is not compulsory under FRR 48/VaR Reporting (page 35): “Registrants, such as those with proprietary concerns about reporting year-end information under the sensitivity analysis and value at risk disclosure alternatives, may report the average, high, and low amounts for the reporting period”.
Table 1
VaR disclosure of top 10 US banks.

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<td>Average VaRDI</td>
<td>0.4</td>
<td>1.8</td>
<td>4.0</td>
<td>4.1</td>
<td>4.9</td>
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<td>3.0</td>
<td>3.4</td>
<td>4.2</td>
<td>3.8</td>
<td>3.5</td>
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<td>0</td>
<td>0</td>
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<td>2</td>
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<td>9</td>
<td>8</td>
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<td>12</td>
<td>12</td>
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<td>70</td>
<td>80</td>
<td>90</td>
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<tr>
<td>Confidence Level</td>
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<td>70</td>
<td>80</td>
<td>80</td>
<td>100</td>
<td>100</td>
<td>100</td>
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<tr>
<td>High, Low, Average VaR</td>
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<td>50</td>
<td>50</td>
<td>60</td>
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<tr>
<td>Year-End VaR</td>
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<td>60</td>
<td>60</td>
<td>70</td>
<td>70</td>
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<td>50</td>
<td>60</td>
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<td>Diversification</td>
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Notes: This table presents some summary statistics about the VaR Disclosure Index (VaRDI) and the percentage of US sample banks that disclose each index component entering into the VaRDI, e.g. a value of 10 means 10% of one bank. VaRDI covers six components of VaR disclosure: (1) VaR Characteristics: score of 1 if Holding Period (e.g. 1 day, 1 month), score of 1 if Confidence Level (e.g. 99%, 95%), (2) Summarized VaR Statistics: score of 1 if High, Low, or Average, score of 1 if Year-End Value, score of 1 if VaR by Risk Category, and score of 1 if Diversification Effect, (3) Intertemporal Comparison: score of 1 if Summarized Information from Previous Year, (4) Daily VaR Figures: score of 1 if Histogram of Daily VaRs, or score of 2 if Plot of Daily VaRs, (5) Trading Revenues: score of 1 if Hypothetical Revenues, score of 1 if Revenues without Trading Fees, score of 1 if Diversification Effect, (3) Intertemporal Comparison: score of 1 if Summarized Information from Previous Year, (4) Daily VaR Figures: score of 1 if Histogram of Daily VaRs, or score of 2 if Plot of Daily VaRs, and (6) Exceptions: score of 1 if Number of Exceptions, or score of 2 if zero exceptions), and score of 1 if Explanation of Exceptions. The range for VaRDI is 0 (minimum)–15 (maximum).

2.2. The evolution of VaR disclosure

In our empirical tests, we use data on the 10 largest US commercial banks. We rank banks according to total assets as of December 31, 2005 which are available on the website of the Board of Governors of the Federal Reserve System. For each sample bank, we collect annual 10-K forms from the SEC-EDGAR website (or from the banks’ websites) over the period 1996–2005.

Table 1 presents the average VaRDI and other descriptive statistics computed across the 10 US banks on each sample year. We first note the very low level of market risk disclosure before the inception of FRR 48 in 1998, which is consistent with Roulstone’s findings (1999). Since then, the amount of market-risk related information released by US banks has increased steadily through time to end up to an average VaRDI in 2005 of seven points (out of 15). We also report a severe discrepancy across banks in terms of disclosure, which is suggested by the large standard-deviation of the VaRDI and the 10-point range between minimum and maximum VaRDIs. Furthermore, the heterogeneity in the level of disclosure remains pervasive during the entire sample period. We believe that some diversity in disclosure levels is to be expected because the size and importance of trading accounts greatly vary across banks (e.g. JPMorgan Chase vs. Sun Trust).

In Fig. 1, we take a disaggregated look at VaR disclosure by plotting the VaRDI time-series for each sample bank. A simple perusal of the 10 panels in this figure allows us to identify some interesting differences across banks. First, the four largest banks display superior market risk disclosure, In particular, top-ranked Bank of America and Wachovia exhibit particularly high VaRDIs compared to their peers. Unlike other banks that have been maintaining a rather constant VaRDI since 1998, these two banks have been steadily improving their communication about market risk. Second, some banks display extremely low levels of disclosure (around 2–3 points).

The lower part of Table 1 displays the percentage of sample banks disclosing each item entering into the calculation of the VaRDI. We see that reporting VaR characteristics and average and/or year-end VaR is now commonplace at US banks. An intriguing result is that some banks do not report the horizon of their VaR estimates although this is a fundamental element of the definition of the VaR. Note that similar results were found in the 1999–2001 surveys conducted by the Basel Committee on Banking Supervision in which 10% (4%) of the surveyed banks did not disclose the holding period (confidence level). Since many different combinations of VaR characteristics can be used (e.g. 1 day/95%, 1 week/99%), displaying a VaR without making explicit its horizon or confidence level is totally meaningless – just like talking about an amount of money without mentioning the currency in which the amount is expressed in. Furthermore, none of the sample banks disclose hypothetical trading revenues adjusted for trading fees over our sample period, which creates complications for backtesting. Finally, we see that plots of actual daily trading revenues and VaRs are reported by at most two banks (depending on the sample year).

As a comparison, we display in Fig. 2 the average VaRDI computed (1) for the 10 largest US commercial banks and (2) for the six largest Canadian commercial banks over the period 1996–2005.13 Interestingly, the smallest US sample bank, State Street, has approximately the same size (defined as total assets) in 2005 as the smallest Canadian sample bank, National Bank of Canada. We collect the annual reports of Canadian banks from the SEDAR website (www.sedar.com). Although we are not aware of any legal requirement in Canada forcing commercial banks to publicly release VaR-related information in their annual reports, VaR disclosure at Canadian banks is significantly higher than at US banks.14 Several potential factors could explain the higher disclosure in Canada. This could be due to the peculiar competitive environment of the Canadian banking industry. Indeed, while the top five US banks in 1999 accounted for just 21% of US deposits, the top five banks in Canada...
accounted for 76% of Canadian deposits (Barth et al., 2001). The higher industry concentration in Canada creates greater incentive for not deviating from the norm, which turns out to be high market risk disclosure. Alternatively, the difference may simply be due to the fact that US banks are primarily exposed to US interest rate risk (where duration measures are sufficient, plus credit risk), while Canadian banks have large exposures to currency risk in their proprietary trading desks.

Fig. 1. VaR Disclosure Index for the top 10 US banks. Notes: This figure plots the VaR Disclosure Index (VaRDI) computed for each of the 10 largest US commercial banks between 1996 and 2005.
2.3. VaR disclosure in the world

How does the level of VaR disclosure in the US and Canada compare with other regulatory jurisdictions? To answer this question we collect data on VaR disclosure from the 2005 annual reports for the 50 largest international banks measured by total assets. The source for the international banks’ assets is Bankersalma-nac.com, which itself takes the data from the banks’ annual reports. We complement this cross-section with our 16 US and 16 Canadian commercial banks and (2) the six largest Canadian commercial banks between 1996 and 2005.

2.4. VaR estimation methods

There are many different methodologies available to compute VaR and under the internal model’s approach banks are afforded significant latitude. In Fig. 4, we summarize the VaR methodology disclosure of our 60 sample banks in their 2005 annual reports. A little over one-third of our sample firms (35.1%) do not disclose the type of internal modeling used to compute VaR which limits the ability of financial statement users to assess the validity of the VaR estimates. At first sight, the high fraction of banks that remain secretive about their proprietary VaR model seems hard to reconcile with the results from the previous surveys of the Basel Committee on Banking Supervision. Indeed, the Basel Committee finds that 96% in 1999 and 2000 and 98% in 2001 of their surveyed banks disclose the type of internal modeling used. However, a careful analysis of the aforementioned surveys shows that the answer ‘VaR’ is counted as an affirmative answer, just like for instance ‘Historical Simulation’. Differently, we require the statistical method used to produce the VaR figures to be specifically mentioned.

We find that almost half of the surveyed banks (47.4%) reported the use of Historical Simulation to compute their VaRs. Put another way, of the 64.9% of firms that disclose their methodology, 73% (≈0.474/(1 – 0.351)) report the use of Historical Simulation. This method is a flexible, non-parametric technique that forecasts future potential price changes using actual shocks on state variables that occurred in the past (Christoffersen, 2003, pp. 100–103; Jorion, 2006, pp. 262–265). The recent popularity of Historical Simulation at commercial banks has been noted by Pritsker (2006), Berkowitz et al. (forthcoming), and Pérignon et al. (2008), though this is the first formal survey of VaR methodology that we are aware of. The second most frequently used VaR method is Monte-Carlo simulation, which is used by 14% of our sample firms.\textsuperscript{15}

The current popularity of Historical Simulation is due to two main reasons. First, the size and complexity of the trading positions at commercial banks make parametric VaR methods hard to implement in practice. As many banks report to be dealing with thousands of risk factors, they choose not to attempt to estimate time-varying volatilities and covariances for risk factors (Andersen et al., 2007). Instead, they implement non-parametric methods, such as Historical Simulation, that can accommodate large-dimensional portfolios without too much exposure to model or estimation risk. Second, banks and regulators want risk market charges to be reasonably smooth through time, without huge changes from one day to the next – and that is exactly what Historical Simulation does (Jorion, 2002b). Since Historical Simulation only relies on the one, sometimes two, year unconditional distribution of the risk factors, it is under-responsive to changes in conditional risk (Pritsker, 2006). A direct consequence of the use of this VaR method is a mechanical disconnection between 1-day VaR and the actual volatility on the next day. We question the empirical validity of this

\textsuperscript{15} The ‘Others’ category includes hybrid VaR methods combining both parametric and non-parametric features (e.g. Historical Simulation with parametric model). Although some banks acknowledge using the variance–covariance or delta-normal method around the year 2000 (e.g. Wachovia and CIBC), it is not the current primary VaR methodology for any of our sample banks.
### Table 2
VaR disclosure in the world.

<p>| Rank | Name               | Country | Assets       | Holding Period | Confidence Level | High, Low, Average | Year-End VaR | Risk Category | Diversification | Previous Year | Histogram Daily VaR | Plot Daily VaR | Hypothetical Revenue | No Trading Fees | Histogram Daily Rev | Plot Daily Revenue | Exceptions | Explanation | VaR DI |
|------|--------------------|---------|--------------|----------------|-----------------|-------------------|--------------|--------------|------------------|---------------|---------------------|----------------|---------------------|----------------|--------------|-------------|--------|
| 1    | Bank of America    | US      | 1,082,243    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 1                   | 0             | 0                   | 0              | 0            | 2           | 0      |
| 2    | JPMorgan Chase     | US      | 1,013,985    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 0                   | 0             | 0                   | 0              | 1            | 0           | 10     |
| 3    | Citigroup          | US      | 706,497      | 1              | 1               | 1                 | 1            | 1            | 1                | 1             | 0                   | 0             | 0                   | 0              | 1            | 0           | 3      |
| 4    | Wachovia           | US      | 472,143      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 0             | 0                   | 0              | 1            | 2           | 0      |
| 5    | Wells Fargo        | US      | 403,258      | 1              | 1               | 1                 | 0            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 3      |
| 6    | US Bank            | US      | 208,867      | 1              | 0               | 0                 | 1            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 2      |
| 7    | Sun Trust          | US      | 177,231      | 1              | 1               | 1                 | 0            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 4      |
| 8    | HSBC Bank          | US      | 150,679      | 1              | 1               | 1                 | 1            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 1            | 0           | 6      |
| 9    | Key Bank           | US      | 88,961       | 1              | 1               | 1                 | 0            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 5      |
| 10   | State Street       | US      | 87,888       | 1              | 1               | 0                 | 0            | 1            | 1                | 1             | 0                   | 0             | 0                   | 0              | 0            | 0           | 2      |
|      |                    |         |              |                |                 |                   |              |              |                  |               |                     |               |                     |                |             |             |        |
| 1    | Royal Bank of Canada | CAN     | 398,981      | 1              | 1               | 1                 | 1            | 0            | 2                | 0             | 1                   | 1             | 1                   | 2              | 0            | 1           | 13     |
| 2    | Toronto Dominion Bank | CAN     | 310,379      | 1              | 0               | 0                 | 0            | 0            | 0                | 2             | 0                   | 0             | 0                   | 0              | 0            | 0           | 4      |
| 3    | Scotiabank         | CAN     | 266,879      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 0             | 0                   | 1              | 1            | 2           | 0      |
| 4    | Bank of Montreal   | CAN     | 252,862      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 0                   | 1              | 1            | 2           | 0      |
| 5    | CIBC (a)           | CAN     | 238,277      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 0                   | 1              | 1            | 2           | 0      |
| 6    | National Bank of Canada | CAN     | 91,444       | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 0                   | 0              | 2            | 1           | 14     |
|      |                    |         |              |                |                 |                   |              |              |                  |               |                     |               |                     |                |             |             |        |
| 1    | Barclay PLC        | UK      | 1,586,879    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 0             | 0                   | 1              | 0            | 2           | 0      |
| 2    | UBS AG             | SWI     | 1,563,282    | 1              | 1               | 0                 | 1            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 4      |
| 3    | BNP Paribas        | FRA     | 1,483,934    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 0                   | 0             | 0                   | 0              | 2            | 2           | 0      |
| 4    | Royal Bank of Scotland | CAN     | 1,300,124    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 0                   | 0             | 0                   | 1              | 0            | 0           | 8      |
| 5    | Agrocole SA        | GER     | 1,251,997    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 0                   | 0             | 0                   | 0              | 0            | 0           | 7      |
| 6    | Deutsche Bank AG   | DE      | 1,170,277    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 0                   | 1              | 1            | 1           | 14     |
| 7    | ABN AMRO Holding NV | NED     | 1,038,929    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 0                   | 0              | 2            | 2           | 0      |
| 9    | Credit Suisse Group | SWI     | 1,016,050    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 0             | 0                   | 1              | 1            | 2           | 0      |
| 11   | Société Générale  | FRA     | 1,000,728    | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 0             | 0                   | 0              | 2            | 2           | 0      |
| 12   | ING Bank NV        | NET     | 983,764      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 2                   | 1             | 1                   | 0              | 0            | 2           | 0      |
| 13   | Banco Santander Centr | SPA     | 954,361      | 1              | 1               | 1                 | 1            | 1            | 1                | 0             | 1                   | 1             | 1                   | 0              | 2            | 2           | 0      |
| 14   | UniCreditO Italian Spa | ITA     | 928,285      | 1              | 1               | 0                 | 1            | 1            | 1                | 0             | 0                   | 1             | 0                   | 0              | 0            | 0           | 2      |
| 15   | Sumitomo Mitsui Banking | JAP     | 916,710      | 1              | 1               | 1                 | 0            | 0            | 0                | 0             | 0                   | 0             | 0                   | 0              | 0            | 2           | 0      |</p>
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<tr>
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</tr>
<tr>
<td>Fortis Bank NV/SA BEL</td>
<td>19</td>
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<tr>
<td>Ind.&amp;Com. Bank of China CHN</td>
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<td>Mizuho Bank UK</td>
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<td>JAP</td>
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<td>The Norinchukin Bank JAP</td>
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<td>Bayerische Hypo-und Ver. GER</td>
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natural consequence of using Historical Simulation in the next section.

3. Quality of VaR disclosure

In this section, we conduct an empirical analysis of the quality of reported VaR estimates. We assess the quality of VaR disclosures using two datasets. The first one is the dataset used in Section 2 and includes year-end VaR figures. The second one includes several years of daily VaRs from five of the largest commercial banks in the world. Both datasets allow us to test whether a VaR model leads to the correct number of exceptions in a given year but only the second (daily) one can assess the ability for a 1-day VaR to forecast the volatility of trading revenue over the next day.

3.1. Backtesting

We begin the empirical analysis by formally testing the null hypothesis that the proportion of exceptions, or days when the actual loss is greater than the 99% VaR, equals 1%. In a sample of daily VaRs at the 99% confidence level, we check whether we observe 0.01 \(\times T\) exceptions. We implement the Likelihood Ratio test of Kupiec (1995) known as the unconditional coverage test:

\[
LR = -2 \ln\left((1-p)^{1-X} + 2 \ln\left((1-p)^{1-X}(p)^X\right)\right),
\]

where \(p = 0.01\) is the target exception rate, \(\hat{p}\) is the sample proportion of exceptions, \(X\) is the total number of exceptions, \(T\) is the total number of observations, and \(LR\) is asymptotically distributed chi-square with one degree of freedom.\(^{16}\)

For each bank, the number of exceptions per year is obtained (when disclosed) from the banks’ annual filings. We display in Table 4 the backtesting results. Consistent with our conclusions in Section 2, we show that the fraction of banks disclosing the exact number of exceptions in a given year has increased over our sample period and remains generally smaller in the US than in the rest of the world. Furthermore, we find that the number of exceptions is extremely small and that, in turn, the null hypothesis is rejected at the 5% confidence level every year but 1998. This is evidence that VaRs disclosed by banks are excessively conservative (see Berkowitz and O’Brien (2002), and Pérignon et al. (2008), for consistent evidence). Interestingly, we do not detect any reduction in VaR overstatement through time, which suggests that the quality of VaR has not improved.

In order to enrich the analysis of the quality of VaR disclosures, we construct a second dataset of daily VaRs and trading revenues. Specifically, we employ a sample of five banks, all of which scored the highest on the disclosure index (all have VaRDIs of at least 13). For each country included in the survey presented in Section 2, we look for a bank disclosing a graph of the daily VaRs and trading revenues over a sufficiently long sample period (2001–2004) whose data can be extracted as we describe below. We start with the largest bank and if its annual report does not include a graph of daily VaRs and trading revenues we then consider the second and then third largest banks. Using this procedure we obtain a sample of five commercial banks from five different countries. In the US, we use the largest bank, Bank of America, since it discloses the necessary information over the period 2001–2004. In Germany and in Canada, we also select the largest bank (Deutsche Bank and Royal Bank of Canada) and pick the second largest bank in Switzerland (Credit Suisse First Boston, hereafter CSFB) and the third largest in France.

\(^{16}\)To compute the LR test statistic when there are no exceptions we use the convention \(0^0 = 1\).
None of the other countries have any banks meeting our data requirements. Trading revenues are not identically defined across our five sample banks. Ideally, disclosed trading revenues should be hypothetical revenues based on previous day portfolio allocation. This is the type of data disclosed by Royal Bank of Canada only. Conversely, Bank of America, CSFB, Deutsche Bank, and Société Générale report actual revenues that are affected by intraday trades made by the bank. Furthermore, none of our sample banks explicitly state that their trading revenues are not inflated by trading fees or commissions, which may create some distortions in backtesting.

Table 3

<table>
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<tr>
<th>Country</th>
<th>World</th>
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<th>GER</th>
<th>UK</th>
<th>CAN</th>
<th>FRA</th>
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<th>CHN</th>
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<th>ITA</th>
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Notes: This table presents some summary statistics about the VaR Disclosure Index (VaRDI) and the percentage of sample banks in the entire sample (‘world’ column) and in each country that disclose each index component entering into the VaRDI. VaRDI covers six components of VaR disclosure: (1) VaR Characteristics: score of 1 if Holding Period (e.g. 1 day, 1 month), score of 1 if Confidence Level (e.g. 99%, 95%), (2) Summarized VaR Statistics: score of 1 if High, Low, or Average, score of 1 if Year-End Value, score of 1 if VaR by Risk Category, and score of 1 if Diversification Effect, (3) Intertemporal Comparison: score of 1 if Summarized Information from Previous Year, (4) Daily VaR Figures: score of 1 if Histogram of Daily VaRs, or score of 2 if Plot of Daily VaRs, (5) Trading Revenues: score of 1 if Hypothetical Revenues, score of 1 if Revenues without Trading Fees, score of 1 if Histogram of Daily Revenues, or score of 2 if Plot of Daily Revenues, and (6) Exceptions: score of 1 if Number of Exceptions, or score of 2 if zero exceptions), and score of 1 if Explanation of Exceptions. The range for VaRDI is 0 (minimum)–15 (maximum). We do not report country-level figures for five countries that only have one sample bank: Australia, Belgium, Denmark, Hong Kong, and Sweden.
Our sample banks use Historical Simulation and Deutsche Bank use a parametric Monte Carlo-based method. All of the banks, except Deutsche Bank, use Historical Simulation by the one percent coverage probability. Three of the banks had the disclosed VaR. The backtesting results are reported in Panel C exceptions which is consistent with the 99% confidence level of the events of September 11. In 2003, there were three exceptions which is consistent with the 99% confidence level of

A brief perusal of the different panels in Fig. 5 suggests that 1-day VaRs do not relate very closely to short-term changes in trading revenue volatility. For example, the VaR for Bank of America during the first and last quarters of 2001 are comparable but the trading volatility following September 11 is much higher. Furthermore, the VaR for Royal Bank of Canada jumps in the third quarter of 2004 while trading return volatility is quite low. This preliminary analysis suggests that there is at best a weak relationship between VaR and subsequent trading volatility.

To provide a benchmark against which bank VaR disclosures can be evaluated, we estimate a simple GARCH model (Bollerslev, 1986) and then an augmented GARCH model, denoted X-GARCH, which includes VaR as a determinant of the conditional variance of trading revenues (Brenner et al., 1996; Donaldson and Kamstra, 2005):

$$h_{t+1} = \alpha + \beta \cdot h_{t-1} + \gamma \cdot \text{VaR}^2_{t+1}.$$ (2)

It is important to note the different information sets used to compute the two volatility measures. When computing VaR, risk-management departments have access to far more information than what is available to the econometrician. In particular, the bank VaR is computed using pseudo-historical portfolio returns, i.e., historical asset returns with the current portfolio weights. On the other hand the econometrician does not have access to current portfolio weights when computing VaR using the GARCH model. The GARCH no exceptions in the sample (4 years for Deutsche Bank and Royal Bank of Canada and 3 years for Société Générale), Bank of America had four exceptions, and CSFB had six exceptions. Because we have around 1000 observations we expect 10 exceptions for all banks but Société Générale which is expected to experience eight exceptions. We can reject the null hypothesis that bank VaR measures have the appropriate coverage for all banks but CSFB. This additional international evidence is consistent with our previous backtesting results based on year-end VaR data.

3.2. In-sample test

To further explore the usefulness of bank VaR disclosures, we proceed with an analysis in which we test the ability of VaR to forecast the volatility of future trading revenues. An intuitive property of a VaR number is that it is positively related to future volatility (since the VaR is a quantile). Under some particular distribution assumptions for the trading revenues, Jorion (2002a,b) and Taylor (2005) show that the relationship between VaR and future volatility should be linear. In fact this result remains valid as long as the distribution falls in the location-scale family. The family is quite broad and includes the normal distribution as well as many asymmetric distributions. For that family, all results are summarized by the mean and the standard-deviation, so it follows trivially that the VaR is described by the first two moments as well.

We also report the methodology used by the banks to construct VaR. All of the banks, except Deutsche Bank, use Historical Simulation and Deutsche Bank use a parametric Monte Carlo-based method which uses the conditional factor covariances. The fact that 80% of our sample banks use Historical Simulation corresponds nicely with the empirical observation in Section 2 that 73% of banks that disclose their methodology use Historical Simulation.

We observe in Fig. 5 that there are relatively few VaR exceptions. For instance, there were zero exceptions for Bank of America in 2002 and 2004 and only one exception in 2001 immediately following the events of September 11. In 2003, there were three exceptions which is consistent with the 99% confidence level of the disclosed VaR. The backtesting results are reported in Panel C of Table 5. All of the banks have fewer exceptions than implied by the one percent coverage probability. Three of the banks had

Fig. 4. VaR calculation methods. Notes: This pie chart displays the relative frequency of each VaR calculation method used by all our sample banks in 2005.

**Footnotes:**

18 The sample period is only 2002–2004 for Société Générale. See the Appendix of the working paper version (http://issn.com/abstract=952595) for a detailed presentation of the data extraction process.

19 Right skewness might reflect fee/commission income for occasional large transactions.

20 If $f(x)$ is any probability density function, then the family of probability density functions $g(x|\mu, \sigma) = 1/\sigma \cdot f((x-\mu)/\sigma)$ is a location-scale family with standard probability density function $f(x)$ and is indexed by the location ($\mu$) and scale ($\sigma > 0$) parameters.

21 In its 2004 annual report, Royal Bank of Canada explains that this VaR spike was triggered by a temporary increase in equity VaR. The latter was caused by higher equity trading inventory arising from equity underwriting activity.

22 There is a possible identification problem that could arise if the banks compute VaR using a GARCH model based on historical actual trading revenues (i.e., using a restricted version of Eq. (2) setting $\gamma = 0$). In this case we could not separately identify $\gamma$ and the GARCH parameters because of perfect collinearity. However, we know that none of our sample banks compute VaR using parametric GARCH models. The model is identified under the joint null hypothesis that $\gamma = 0$ and bank VaR is imperfectly correlated with $h_{t+10}$ and when the GARCH model is miss-specified (i.e., $x = \beta = 0$). Incidentally, we find quite low correlation between bank VaR and GARCH-based fitted volatility.
model is estimated using historical portfolio returns and pseudo-re-
turns which are in turn based on historical and not current portfolio
weights. This is a key difference since trading positions can vary
dramatically from one day to the next.

We begin our analysis by restricting the \( \gamma \) parameter in Eq. (2)
to be zero and estimating the standard GARCH model. We report
the parameter estimates and standard errors for this model for
all five banks in Table 6. Volatility shocks are very persistent for
Bank of America and CSFB, but they are significantly less persistent
for the other three banks. In fact we cannot reject the null hypo-
thesis that \( \alpha = 0 \) for Société Générale, though all other estimates of \( \alpha \)
are at least two standard errors from zero. The estimates of \( \gamma \) are
between 0.125 and about 0.2, all highly statistically significant,
and imply a \( T \) distribution with between five (=0.2 \( \gamma \)) and eight
(=0.125 \( \gamma \)) degrees of freedom. We only need to include autocorre-
lation in the conditional mean for Deutsche Bank.

We next turn our attention to testing the usefulness of VaR
measures for forecasting conditional volatility and estimate the
augmented GARCH model including the \( \gamma \) coefficient. For all banks
using Historical Simulation, the improvement in model fit after
including VaR is trivial and the point estimates of \( \gamma \) are insignifi-
cant. Interestingly, it is only significant for Deutsche Bank, which
is the only bank that relies on a parametric VaR methodology.23
The difference between the usefulness of VaR by Deutsche Bank
and the other four banks is compelling evidence about the discon-
nection between Historical Simulation VaR and actual future
volatility.

3.3. Out-of-sample test

We also evaluate the performance of VaR and GARCH forecasts
using the Mincer and Zarnowitz (1969) regression:

\[
R_{t+1} = \mu + \epsilon_{t+1},
\]

\[
h_{t+1 \gamma} = \alpha + \gamma \cdot \epsilon_t^2 + \beta \cdot h_{t-1 \gamma},
\]

where the conditional variance of trading revenues, \( h_{t+1 \gamma} = \mathbb{E}(\epsilon_{t+1 \gamma}^2) \),
is modeled as a GARCH process with standardized innovations that
are \( T \) random variables, which nests the Gaussian GARCH model as a
special case. To forecast time \( t + 1 \) conditional variance, \( h_{t+1 \gamma} \),
we estimate the parameters using all observations up to and includ-
ing time \( t \). We then extend the Mincer–Zarnowitz regression to also
include the GARCH forecasts:

\[
R_{t+1} = \alpha + b \cdot \text{VaR}^2_{t+1 \gamma} + c \cdot h_{t+1 \gamma} + \epsilon_{t+1}.
\]

Note that if the GARCH model is true, then \( c \) will equal unity, while
if the VaR model is the correct one \( b \) will be positive, but without
knowing the true conditional distribution we cannot pin down a specific
value for \( b \).

We report the variance forecasting regression coefficients and
\( R^2 \) in Table 7 for the years 2002–2004.24 When we only include
the VaR-based forecast, we obtain positive but insignificant coeffi-
cients for Bank of America, CSFB and Deutsche Bank, and negative
and insignificant results for Royal Bank of Canada and Société Géné-
rale. In contrast with Jorion (2002a), we find no support for the
hypothesis that VaR figures are correlated with the future volatility
of trading revenues. Furthermore, the \( R^2 \) are generally small but typ-
ical for this type of regression since squared trading revenue is a
noisy proxy for the true volatility (Andersen and Bollerslev, 1998).
When we only use the step-ahead conditional volatility forecast
from a GARCH model, we find a positive relationship for all banks
(though not significant for Deutsche Bank) except Société Générale
which is negative and statistically insignificant.25 Including both
GARCH and VaR to forecast volatility generally lowers the magnitude
of the \( b \) and \( c \) coefficient estimates, suggesting that the two esti-
mates are generally complementary since Historical Simulation
misses volatility clustering and the GARCH model ignores changes

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23 An alternative interpretation of the results for Deutsche Bank is that the bank risk
exposure changes much more dramatically than other banks, and it is information
about changing position size that is picked up by the \( \gamma \) coefficient in the regressions.

24 We drop the first year since we use a 1-year estimation window for the GARCH

25 We use the first year’s data (2001) to estimate a GARCH model and use the
parameter estimates to forecast volatility for the subsequent day’s trading revenue.
We then expand the sample using that observation, re-estimate the GARCH model
parameters using this slightly larger sample, and forecast the next day’s trading
revenue variance. To interpret the puzzling result for Société Générale recall that the
estimate of \( \alpha \) in Table 6 was very small and not statistically different from zero so its
poor performance out-of-sample is not surprising.
in the portfolio composition. Our main conclusion from the out-of-sample test is, unlike the GARCH estimate, 1-day VaR does not forecast trading revenue volatility.

Given the results in Table 7, it seems premature to conclude that the parametric VaR method used by Deutsche Bank is unambiguously superior to that of competing banks. In particular, Deutsche Bank does not outperform Bank of America in terms of explanatory power or t-stats. Part of the results may be driven by the nature and properties of the trading revenue data. For example, the high autocorrelation in the trading revenues of Deutsche Bank may affect the relationship between VaR estimates and squared returns.

Fig. 5. Daily Value-at-Risk and trading revenues. Notes: This figure displays the daily VaR (lower line) and trading revenues (upper line) of Bank of America (top panel), Credit Suisse First Boston, Deutsche Bank, Royal Bank of Canada, and Société Générale (lowest panel) between January 1, 2001 and December 31, 2004. All values are in millions and are expressed in local currencies.
4. Conclusion

In most countries, commercial banks are required to publicly disclose quantitative information about their trading risks and VaR is the most popular choice. In the first part of this paper, we document a general upward trend in the quantity of information released by commercial banks to the public over the past decade. We also find that Historical Simulation is by far the most popular VaR methodology used by commercial banks. We postulate that the current popularity of Historical Simulation among banks leads...
to a mechanical disconnection between 1-day VaR and future volatility.

In the second part of the paper, we empirically assess the quality of VaR disclosure. We find that VaRs are excessively conservative and that their quality did not improve over time. Furthermore, we test whether daily VaRs contain information about the volatility of subsequent trading revenues. The different econometric approaches implemented in this paper all suggest that bank VaR computed using Historical Simulation helps little in forecasting the volatility of future trading revenues. In addition, its incremental forecasting ability over a simple GARCH model is very limited. Interestingly, the only bank for which we have been able to find some evidence of volatility forecasting ability is the one only not using Historical Simulation. Our empirical findings are consistent with our assertion that there is disconnect between Historical Simulation-based VaR and future volatility.

Although there is a general belief that more information is better, investors, creditors, and other users of VaR information are primarily concerned with accuracy. Given the overall poor performance of actual VaR forecasts reported in this paper (and in previous literature), it seems questionable to systematically use firm-level VaR as the basis of regulatory capital requirement, through the market risk charge.

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