The Level and Quality of Value-at-Risk Disclosure by Commercial Banks

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Following a string of high profile trading losses, greater attention has recently been focused on the trading risk faced by commercial banks. Following the 1996 Market Risk Amendment to the Basel Accord (Basel Committee on Banking Supervision, 1996), the US and many other international bank regulatory agencies have set capital requirements to include a market risk charge that reflects the risk of banks' trading activities. The amount of capital required is a direct function of the bank's Value-at-Risk (hereafter VaR) from trading activities. VaR is defined as the p-th lower tail percentile of trading revenue over the next h periods $R_{t,t+h}$, formally $p = \Pr(R_{t,t+h} < VaR_{t+h|t})$, and has become a standard market risk measure (Jorion, 2006).

In the U.S., market risk disclosures are required 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 the three reporting methods described in FRR 48 (Linsmeier and Pearson, 1997).[1] A not so well-known consequence of this multi-format disclosure environment is that VaR disclosures are not mandatory for all 10-K filings as long as an alternative quantitative disclosure format is used. In practice, the level of disclosure about trading

[1] 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, Lamb and Schroeder, 2000 for an illustration).

activities and the associated VaR varies greatly across banks. For instance in 2005, some US banks report only year-end VaR or average VaR, while other US banks are more forthcoming and include time-series plots of both daily VaRs and trading revenues.

The goal of this paper is two-fold. The first objective is to study the actual level of VaR disclosure in the U.S. since the 1996 Market Risk Amendment to the Basel Accord. For the ten largest US banks, we compute an annual VaR Disclosure Index (hereafter VaRDI) that aims to capture the numerous facets of market risk. Specifically, VaRDI has 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 VaR, (4) a histogram or plot of daily VaRs, (5) definition of trading revenues (hypothetical revenues and non-inclusion of trading fees) and a histogram or plot of daily trading revenues, and (6) backtesting (the number of exceptions, i.e., days when actual loss is greater than VaR, and explanations of these exceptions). Over the period 1996-2005, we find large differences in the level of disclosure across US banks and an overall upward trend in the quantity of information released to the public. We also show that, over this ten-year sample period, disclosures at US banks are considerably lower than disclosures at Canadian banks. Moreover, we compute the value of our disclosure index in 2005 for a sample of 60 US and international banks. This cross-sectional analysis of the largest banks in the world indicates that US disclosures are below the average, although some banks, such as Bank of America and Wachovia, score very high on our 15-point disclosure scale. Furthermore, we uncover some drastic differences in disclosure across regions: from an overall satisfactory disclosure in Europe and Canada to absolutely no VaR disclosure in China.

Furthermore, we find that Historical Simulation is the most popular VaR method in the world, as 73 percent of banks that disclose their VaR method report using Historical Simulation. This is a non-parametric method based on the unconditional distribution of the risk factors. We show that a direct implication of the current popularity of historical simulation is that 1-day VaR is likely to be disconnected from the next day volatility.

Our second objective is to assess the accuracy of the disclosed VaR figures. Specifically, we 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 revenue and, as a result, will increase with the conditional volatility. In fact, we show theoretically that VaR is linearly related to the conditional standard deviation of trading revenue. 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 compare these two 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 based on Historical Simulation helps little in forecasting future volatility. In addition, its incremental forecasting ability over a simple GARCH model is often negligible. This finding is consistent with our claim that Historical-Simulation VaRs are disconnected from future volatility.

Our paper makes two contributions to the literature on financial risk management. Firstly, we conduct the first survey of actual disclosures in the U.S. over the entire post-1996 Market Risk Amendment period. We also compare US practices with those in other countries using data from a cross-section of international banks.[2] Our sample size (60 banks in total) is larger than the one used by the Basel Committee on Banking Supervision (2001, 2002, and 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.

Secondly, we provide new evidence on the accuracy (or lack of) of actual VaR models used at commercial banks. Unlike the few empirical studies examining the accuracy of actual VaRs figures (Berkowitz and O'Brien, 2002, Berkowitz, Christoffersen and Pelletier, 2006, and Pérignon, Deng and Wang, 2006), we do not only rely on backtesting, which is known to lack statistical power (Jorion, 2006). Instead, we formally test whether disclosed VaRs are useful in forecasting the conditional volatility of trading revenues. 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 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.[3] Our analysis differs from Jorion's (2002a) study since we use higher frequency data, namely daily

[2] In an independent study, Hirtle (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.

[3] Hirlte (2003) shows that US banks' quarterly market risk charges contain valuable information about future risk exposures. See Liu, Ryan and Tan (2004) for a follow-up paper of Jorion (2002a).

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.

We claim that the *level* and the *quality* of VaR public disclosure should not be studied in isolation. Previous research typically focuses either on the "quantity aspect" of VaR disclosures (e.g. Roulstone, 1999, and Basel Committee on Banking Supervision's 1999-2001 surveys) or the "quality aspect" of VaR disclosures (e.g. Pérignon, Deng and Wang, 2006), but not on both simultaneously.[4] However, as the primary purpose of financial reporting is decision usefulness (FASB, 1980), it is very important to check whether the quantity of information and the accuracy of this information are both at acceptable levels. Furthermore, meaningful disclosure, as part of market discipline, is one of the three essential foundations or pillars of Basel II. Even a strict compliance to the most stringent disclosure requirement will be of little help in reducing information asymmetry on the market if the disclosed information is measured with error or biased. As Hoppe (1998, page 50) puts it, "believing a spuriously precise estimate of risk is worse than admitting the irreducible unreliability of one's estimate. False certainty is more dangerous than acknowledged ignorance".

Studying empirically the accuracy of disclosed VaR figures based on proprietary models is also 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 and Hendricks and Hirtle, 1997), the capital charge for market risk is based on the output of a bank's internal VaR model rather than on an externally imposed supervisory

[4] Berkowitz and O'Brien (2002) and Berkowitz, Christoffersen and Pelletier (2006) also analyze the accuracy of VaR computed by commercial banks, but their VaR figures were not publicly disclosed. Their series are normalized to protect the banks' anonymity.

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 (Daníelsson, Jorgensen and de Vries, 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, very little is known on the actual accuracy of disclosed VaRs.

The rest of the paper is organized as follows. In Section I, we study the level of VaR disclosure at commercial banks in the U.S. 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 II presents our empirical analysis of the relationship between VaR and the volatility of future daily trading revenues. We summarize and conclude our study in Section III.

I. Level of VaR Disclosure

In the U.S. 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.

A. VaR Disclosure Index

To facilitate the empirical analysis we construct a disclosure index, the 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.

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

4. Daily VaR Figures

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

6. Backtesting

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 (page 33) that "*average 1-day VARs 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 (page 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 (page 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).[5] The reason is that histograms remain silent about the dynamics of daily VaRs and do not permit 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

[5] 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).

and trading revenues are superimposed, one can easily detect any exceptions or bunches of exceptions.

Information on trading revenues is also central to the construction of the index.[6] 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 (page 60) tells investors that "*Daily back-testing against <u>hypothetical</u> 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 (page 157) states "*In addition to using actual results for backtesting, ING also uses hypothetical results, which measures results excluding the effect of intraday trading, <u>fees and commissions</u>*". 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, page 65): "*actual market risk-related losses exceeded VaR measures one day out of 250 total trading days. This occurred*

[6] See Berkowitz and O'Brien (2007) and Jorion (2007) for some empirical evidence on the (joint) dynamics of US banks' trading revenues.

immediately following the events of September 11, 2001 due to extreme market conditions" or JP Morgan (annual report 2001, page 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 to not 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).[7] 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.[8] 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 I-D below.

[7] Being excessively conservative when setting VaR can be an issue for backtesting purposes (see Pérignon, Deng and Wang, 2006) but not from a disclosure point of view.

[8] 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".

B. The Evolution of VaR Disclosure

In our empirical tests, we use data on the ten 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 and annual reports from the banks' websites (or hardcopies directly from the banks) over the period 1996-2005. For most banks, there is a perfect overlap between the two documents as far as market risk and VaR are concerned. However, 10-K forms sometimes directly refer to annual reports for market risk disclosure. In the following, we do not make any distinction between information disclosed in 10-K forms and in annual reports.

Table I presents the average VaRDI and other descriptive statistics computed across the ten 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 fifteen). 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.

In Figure 1, we take a disaggregated look at VaR disclosure by plotting the VaRDI time-series of each sample bank. A simple perusal of the ten panels in this figure allows us to identify some interesting differences across banks. Firstly, 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. Secondly, some banks display surprisingly low levels of disclosure. For instance, the scores for Wells Fargo and U.S. Bank are around 2-3 points. This result is particularly puzzling given the fact that a minimal compliance with FRR 48 would lead to a four-point VaRDI. However, as already mentioned, as long as a US bank furnishes quantitative information about market risk based on a tabular presentation and/or sensitivity analysis, it does not have to disclose any information about its VaR.

The lower part of Table I 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. one day/95%, one 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 Figure 2 the average VaRDI computed (1) for the ten largest US commercial banks and (2) for the six largest Canadian commercial banks over the period 1996-2005.[9] 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 the 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 excellent and significantly higher than at US banks.[10] We think that the higher disclosure in Canada is due, at least partly, to the peculiar competitive environment in this country. While the Top five US banks in 1999 accounted for just 21 per cent of US deposits, the Top five in Canada were much more dominant, accounting for 76 per cent of Canadian deposits (Barth, Caprio, and Levine, 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.[11]

C. VaR Disclosure in the World

How does the level of VaR disclosure in the U.S. and Canada compare with other regulatory jurisdictions? To answer this question we collect data on VaR disclosure from the 2005 annual reports for the fifty largest international banks measured by total assets.

[9] The six Canadian banks are Bank of Montreal, Bank of Nova Scotia or Scotiabank, Canadian Imperial Bank of Commerce, National Bank of Canada, Royal Bank of Canada, and Toronto-Dominion Bank. Bank size is defined as total assets at the end of the year 2005 as disclosed in banks' annual reports. The term "Big Six" is frequently used to refer to the six biggest banks that dominate the banking industry in Canada.

[10] The Office of the Superintendent of Financial Institutions (OSFI), the financial regulatory body in Canada, made compulsory VaR calculations in 1997, but not VaR public disclosures.

[11] Another implication of the high concentration of the Canadian banking industry is that all banks are likely to be very cautious when estimating their VaR. Consistent with this assertion, Pérignon, Deng and Wang (2006) show that the six largest Canadian commercial banks strongly overstate their VaR, which leads in some cases to market risk charges that are five times larger than what would be required with unbiased VaR estimates.

The source for the international banks' assets is Bankersalmanac.com, which itself takes the data from the banks' annual reports. We complement this cross-section with our 16 US and Canadian banks for which we have data over a longer sample period. Since some of the banks included in the world Top 50 are incorporated in the U.S. or in Canada, we end up with 60 banks. Table II presents for each sample bank the name, the country of origin, the value of each item entering into the calculation of the VaRDI, and the bank's VaRDI. To ease the comparison among the level of disclosure of the different banks, we plot in Figure 3 the VaRDI of all non-US, non-Canadian banks included in the world Top 50, sorting the banks from the biggest (bank #1), Barclay, to the smallest (bank #50), National Australia Bank. Several interesting features about international VaR disclosure can be identified in Figure 3. Firstly, consistent with the evidence in the U.S., there is considerable cross-sectional variation in the disclosure of large international banks. Secondly, the level of disclosure is higher for banks ranked in the first half of the sample (average VaRDI of 9.1 for Top 25 banks) than for smaller banks (average VaRDI of 6.5 for banks ranked between 26th and 50th). According to a two-sample t-test assuming unequal variances, these two means are statistically different at the 5% confidence level. Thirdly, average disclosure at US banks is slightly lower than the average disclosure at international banks, i.e., average VaRDI of 7.0 for large US banks and 7.8 for large international banks, and as already noted, much lower than in Canada (average VaRDI of 12.0 for Canadian banks).

In order to investigate further the differences in VaR disclosure across countries, we present in Table III several country-specific statistics about VaR disclosure and the percentage of banks disclosing each VaRDI component. Our first finding is that overall VaR disclosure at US commercial banks is not that different from what is currently done in Germany, UK, France, Japan, Italy, Spain, or Switzerland, although the small number of banks in some countries clearly weakens our conclusion. However, US banks appear more reluctant to reveal the more sensitive and meaningful dimensions of VaR information: only 20% of our US sample banks plot the daily VaRs and daily trading revenues and 40% disclose the actual number of exceptions, whereas the equivalent percentages are 48%, 32%, and 52% in our world sample. Furthermore, it appears that Canada, the Netherlands, and Spain are positive outliers in the world of VaR disclosure. Finally, none of the four Chinese commercial banks in the Top 50 list released any VaR related information in 2005. However, as they go public on developed stock exchanges, like the Bank of China in 2006 on the Hong Kong Stock Exchange, Chinese banks will likely improve their market risk disclosure to facilitate salability of their financial assets.

D. 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 Figure 4 we summarize the VaR methodology disclosure by our 60 sample banks in their 2005 annual reports. A little over one-third of sample firms that disclose their VaR (i.e., 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 known.

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, pages 100-103, and Jorion, 2006, pages 262-265). The recent popularity of Historical Simulation at commercial banks has been noted by Berkowitz, Christoffersen and Pelletier (2006), Pérignon, Deng and Wang (2006) and Pritsker (2006), 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.[12]

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, Bollerslev, Christoffersen and Diebold, 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

[12] 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.

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 natural consequence of using Historical Simulation in the next section.

II. Quality of VaR Disclosure

In this section we conduct an empirical analysis of the quality of reported VaR estimates. We assess the quality using daily VaR measures from five of the largest commercial banks in the world. We define 'VaR quality' as the ability for a VaR to forecast the volatility of trading revenues.

A. Data and Backtesting

For our empirical analysis of the quality of VaR disclosures 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 I, 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 this 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 U.S., 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 (i.e., Deutsche Bank and Royal Bank of Canada, respectively) and pick the second largest bank in Switzerland (Credit Suisse First Boston, hereafter CSFB) and the third largest in France (Société Générale). None of the other countries have any banks meeting our data requirements. One may be concerned about how representative our sample is. We note that including a plot of VaR and trading revenue is voluntary and we focus on only the largest banks which presumably devote the most resources to computing VaR. Consequently, our results are tilted towards finding that disclosed VaR is useful. However, to pre-empt our results, we find that VaRs disclosed by most of these banks are not very helpful to forecast variability of future trading revenues.

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.

For the five sample banks, we upload the VaR graph from the annual report for the years 2001-2004 in our data extraction application and retrieve the underlying time series.[13] We present the graphs of the daily trading revenues and one day-ahead 99% VaRs in Figure 5. We observe that there are relatively few exceptions or days when the actual loss is greater than the VaR. 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. This is despite the fact that in a sample of 250 daily VaRs at the 99%

[13] The sample period is only 2002-2004 for Société Générale. See the Appendix for a detailed presentation of the data extraction process.

confidence level one would expect to observe two to three exceptions every year. In 2003, there were three exceptions which is consistent with the 99% confidence level of the disclosed VaR.

A brief perusal of the different panels in Figure 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.[14] This preliminary analysis suggests that there is at best a weak relationship between VaR and subsequent trading volatility.

We present in Table IV the summary statistics of daily trading revenues (Panel A) and VaRs (Panel B). We observe that the magnitude of trading activities varies across banks with Deutsche Bank having an average trading revenue of €41 million per day which is several times larger than the other banks. Trading revenues are also highly volatile with extreme profits and losses, right skewed, more leptokurtic than the normal distribution, and exhibit ARCH effects.[15] There is evidence of modest autocorrelation around 5 to 10 percent for all banks except Deutsche Bank which is over 40 percent. The Augmented Dickey-Fuller test indicates that all five banks trading revenues are stationary. This preliminary analysis suggests that a GARCH model – especially if it is based on a statistical distribution that accommodates fat tails, e.g. a T distribution – should be able to appropriately model the dynamics of the conditional volatility of trading revenues. In

[14] 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.
[15] Right skewness might reflect fee/commission income for occasional large transactions.

Panel B, we report summary statistics for the VaR figures. As a visual inspection of Figure 5 indicates, VaRs are strongly autocorrelated, as expected for a second moment.

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 uses a parametric Monte Carlo-based method which uses the conditional factor covariances. The fact that 80 percent of our sample banks use Historical Simulation corresponds nicely with the empirical observation in Section I that 72 percent of banks that disclose their methodology use Historical Simulation.

We begin the empirical analysis by formally testing the null hypothesis that the proportion of exceptions equals one percent using the banks' VaRs. We implement the Likelihood Ratio test of Kupiec (1995) known as the unconditional coverage test:

$$LR = -2\ln\left\{(1-p)^{T-X} p^{X}\right\} + 2\ln\left\{(1-\hat{p})^{T-X} (\hat{p})^{X}\right\} \tag{1}$$

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] The results are reported in Panel C of Table IV. All of the banks have fewer exceptions than implied by the one percent coverage probability. Three of the banks had no exceptions in the sample (four years for Deutsche Bank and Royal Bank of Canada and three years for Société Générale) and Bank of America had four exceptions and CSFB had six exceptions. Because we have around 1,000 observations we expect ten 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

[16] To compute the LR test statistic when there are no exceptions we use the convention $0^0 = 1$.

CSFB. The international evidence of VaR overstatement presented here is consistent with US evidence in Berkowitz and O'Brien (2002) and Canadian evidence in Pérignon, Deng and Wang (2006).

B. In-Sample Test

To further explore the usefulness of bank VaR disclosures we proceed with a conditional analysis in which we test the ability of VaR to forecast the conditional volatility of future trading revenues. We exploit the link between conditional volatility and VaR to develop a specification test for bank's internal VaR models. To link VaR and conditional volatility recall the relationship between the cumulative distribution functions of two random variables x and y linked by the monotonically increasing function $y = g(x)$ (Theorem 2.1.1, Casella and Berger, 1990):

$$F_Y(y) = F_X(g^{-1}(y)). \tag{2}$$

The VaR for portfolio y is defined by:

$$p = F_Y(VaR_Y). \tag{3}$$

Equating Equations (2) and (3) and solving for the VaR of portfolio x gives $VaR_x = g^{-1}(VaR_y)$, from which we obtain:

$$VaR_Y = g(VaR_X). \tag{4}$$

One special case is of particular interest. If x is a standardized random variable (i.e., zero mean and unit standard deviation) and $y = g(x) = \mu + \sigma \cdot x$, $\sigma > 0$ (i.e., a member of the location-scale family of distributions), then:[17]

[17] If $f(x)$ is any probability density function, then the family of probability density functions $g(x|\mu,\sigma) = 1 / \sigma \times f((x-\mu) / \sigma)$ is a location-scale family with standard probability density function $f(x)$ and is indexed by the location (μ) and scale ($\sigma > 0$) parameters. The normal distribution is a member in which $f(x)$ is the standard

$$VaR_Y = \mu + \sigma \cdot VaR_X. \tag{5}$$

Holding the conditional mean constant, this suggests that the VaR is larger during periods of high volatility, and the relationship between VaR and standard deviation is linear. This result extends a similar result in Jorion (2002a) who assumes a symmetric conditional distribution with time-varying heteroscedasticity:

$$VaR_{t+1|t} = \sqrt{h_{t+1|t}} Z_p \tag{6}$$

where Z_p denotes the p-th percentile of the symmetrically distributed random variable Z.[18]

To provide a benchmark against which bank VaR disclosures can be evaluated, we estimate a simple GARCH model and then an augmented GARCH model, denoted X-GARCH, which includes VaR as a determinant of the conditional variance of trading revenues (Brenner, Harjes and Kroner, 1996 and Donaldson and Kamstra, 2005):[19]

$$h_{t+1|t} = \omega + \alpha \cdot e_t^2 + \beta \cdot h_{t|t-1} + \gamma \cdot VaR_{t+1|t}^2. \tag{7}$$

It is important to note the different information sets used to compute the two volatility measures. When computing VaR the risk-management departments have access to far

normal probability density function, and the location and scale parameters are respectively the mean and standard deviation, though the location and scale parameters are not always the mean and standard deviation. The family is quite broad and includes many asymmetric distributions.

[18] The link between conditional standard deviation and VaR holds even when portfolio returns are asymmetric as long as the conditional distribution falls in the location-scale family of distributions. For example, the relationship holds when there is skewness but the standardized skewness is constant (though the conditional third central moment can vary through time as volatility changes). In our parametric empirical tests we use the fat-tailed T distribution to account for leptokurtosis.

[19] 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 Equation (7) setting $\gamma = 0$). In this case we could not separately identify γ 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 $h_{t+1|t}$ and when the GARCH model is miss-specified (i.e., $\alpha = \beta = 0$). Incidentally, we find quite low correlation between bank VaR and GARCH-based fitted volatility.

more information than what is available to the econometrician. In particular, the bank VaR figure 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 model is estimated using historical portfolio returns and pseudo-returns which are in turn based on historical and not current portfolio weights. This is a key difference since portfolios vary dramatically from one day to the next.

We begin our analysis by restricting the γ parameter in Equation (7) 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 V. 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 hypothesis that $\alpha = 0$ for Société Générale, though all other estimates of α are at least two standard errors from zero. The estimates of ν are between 0.125 and about 0.2, all highly statistically significant, and imply a T distribution with between five ($=0.2^{-1}$) and eight ($=0.125^{-1}$) degrees of freedom. We only need to include autocorrelation 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 γ coefficient. For all banks using Historical Simulation, the improvement in model fit after including VaR is trivial and the point estimates of γ are insignificant. Interestingly, it is only significant for Deutsche Bank, which is the only bank that relies on a parametric VaR methodology. The difference between the usefulness of VaR by Deutsche Bank and the other four banks is compelling evidence about the disconnection between Historical Simulation VaR and actual future volatility.

C. Out-of-Sample Test

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

$$R_{t+1}^2 = a + b \cdot VaR_{t+1|t}^2 + u_{t+1} \tag{8}$$

where R_{t+1} is the trading revenue on day $t+1$, and $VaR_{t+1|t}$ is the step-ahead VaR estimate made on day t for day $t+1$ trading revenue. It is important to note that different distributions will generate different values for Z_p in Equation (6) but the regression coefficient b will automatically adjust for these differences.

To provide a benchmark against which the VaR volatility forecasts can be evaluated, we consider a simple GARCH model for daily trading revenues:

$$y_{t+1} = \mu + e_{t+1} \tag{9}$$

$$h_{t+1|t} = \omega + \alpha \cdot e_t^2 + \beta \cdot h_{t|t-1} \tag{10}$$

where the conditional variance of trading revenues, $h_{t+1|t} = E_t\left(e_{t+1}^2\right)$, 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, $h_{t+1|t}$, we estimate the parameters using all observations up to and including time t. We then extend the Mincer-Zarnowitz regression to also include the GARCH forecasts:

$$R_{t+1}^2 = a + b \cdot VaR_{t+1|t}^2 + c \cdot h_{t+1|t} + u_{t+1}\,. \tag{11}$$

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 VI for the years 2002-2004.[20] When we only include the VaR-based forecast, we obtain positive but insignificant coefficients for Bank of America, CSFB and Deutsche Bank, and negative and insignificant results for Royal Bank of Canada and Société Générale. 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 for these regressions are generally small. Taking Bank of America as an example we find that VaR generates a small R^2 of around 0.44 percent. To assess the significance of this coefficient we compare it to the out-of-sample forecasts from GARCH models (Bollerslev, 1986).[21] Interestingly, the R^2 from the GARCH-only forecasts is slightly higher than for the VaR only regressions (e.g., 0.55 percent for Bank of America). Including both GARCH and VaR to forecast volatility increases the R^2 and generally lowers the magnitude of the *b* and *c* coefficient estimates, suggesting that the two estimates are generally complementary since Historical Simulation misses volatility clustering and the GARCH model ignores changes in the portfolio composition. Our main conclusion from the out-

[20] We drop the first year since we use a one-year estimation window for the GARCH model. The sample period is 2003-2004 for Société Générale.

[21] 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. When we only use the step-ahead conditional volatility forecast from the 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. To interpret the puzzling result for Société Générale recall that the estimate of α was very small and not statistically different from zero so its poor performance out-of-sample is not surprising.

of-sample test is, unlike the GARCH estimate, 1-day VaR does not forecast trading revenue volatility.

III. Conclusion

In most countries, commercial banks are required to publicly disclose quantitative information about their trading risks with VaR being the most popular. In the first part of this paper, we study actual VaR disclosures both in the U.S. and internationally. Over the period 1996-2005, we find some large differences in the level of disclosure across US banks and a general upward trend in the quantity of information released to the public. Our cross-sectional analysis of 60 international banks indicates that US disclosures are below the average and we uncover some drastic differences in disclosure across regions: from an overall satisfactory disclosure in Europe and Canada to absolutely no VaR disclosure in China. 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 disconnection between 1-day VaR and actual future volatility.

In the second part of the paper, we empirically test whether actual daily VaRs contain information about the volatility of subsequent trading revenues. Using publicly available trading revenues and VaR presented in banks' annual reports, we compare the forecasting ability of the VaR computed by the bank with volatility forecasts from a simple GARCH model. 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 sample bank (i.e., Deutsche Bank) for which we have been able to find some evidence of volatility forecasting ability is the only one not using the Historical Simulation technique. Our empirical findings are consistent with our assertion about the disconnection between Historical Simulation VaR and future volatility.

There are however some alternative explanations for our findings. Firstly, our five sample banks may not be representative of all commercial banks. It is conceivable that we have simply selected the worst performing banks. Although we cannot definitively rule out this possibility, we do not think that it is very likely since the five sample banks were selected because (unlike most other major banks) they voluntarily disclose daily VaR and trading revenue in their annual reports. They are also among the largest banks in the world and, as a result, have more resources to devote to market risk measurement than the average bank. Secondly, the disclosed trading revenues that we use in this paper include trading fees, which may cloud the relationship between VaR and future volatility. Given the scarcity of the available data, we are currently unable to properly disentangle the different effects and further research is certainly warranted.

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Table I: VaR Disclosure of Top 10 US Banks

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Average VaRDI	0.4	1.8	4.0	4.1	4.9	6.3	6.7	6.5	7.0	7.0
Standard Deviation VaRDI	1.3	2.9	3.2	3.0	3.4	4.2	3.8	3.5	3.7	3.7
Minimum VaRDI	0	0	0	0	0	0	2	2	2	2
Maximum VaRDI	4	8	9	8	10	12	12	12	13	13
Holding Period	10	40	70	70	70	80	90	90	90	90
Confidence Level	0	40	70	80	80	90	100	100	100	100
High, Low, Average VaR	0	0	40	40	50	50	60	60	80	80
Year-End VaR	0	10	50	50	60	60	70	70	80	80
Risk Category	0	20	40	40	50	60	60	60	60	60
Diversification	0	20	50	30	40	50	40	40	40	40
Previous Year	0	0	40	60	60	50	60	60	60	60
Histogram Daily VaR	0	0	10	10	10	10	10	0	0	0
Plot Daily VaR	0	0	0	0	10	20	20	20	20	20
Hypothetical Trading Revenue	0	0	0	0	0	0	0	0	0	0
No Trading Fees	0	0	0	0	0	0	0	0	0	0
Histogram Daily Trading Revenue	10	10	10	10	20	40	40	50	50	50
Plot Daily Trading Revenue	0	0	0	0	10	20	20	20	20	20
Exceptions	10	20	20	10	10	40	40	40	40	40
Explanation of Exceptions	0	0	0	0	0	30	0	0	0	0

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% or 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 Histogram of Daily Revenues, or score of 2 if Plot of Daily Revenues), and (6) 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).

Table II: VaR Disclosure in the World

Rank	Name	Country	Assets	Holding Period	Confidence Level	High, Low, Average	Year-End VaR	Risk Category	Diversifica-tion	Previous Year	Histogram Daily VaR	Plot Daily VaR	Hypothetical Revenue	No Trading Fees	Histogram Daily Rev.	Plot Daily Revenue	Exceptions	Explanation Exceptions	**VaRDI**
Panel A: US Banks																			
1	Bank of America (7)	US	1,082,243	1	1	1	1	1	1	1	0	2	0	0	1	1	2	0	**13**
2	JPMorgan Chase (10)	US	1,013,985	1	1	1	1	1	1	1	0	0	0	0	1	0	2	0	**10**
3	Citigroup (18)	US	706,497	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	**8**
4	Wachovia (36)	US	472,143	1	1	1	1	1	0	1	0	2	0	0	1	1	2	0	**12**
5	Wells Fargo (40)	US	403,258	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**3**
6	U.S. Bank	US	208,867	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	**2**
7	Sun Trust	US	177,231	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	**4**
8	HSBC Bank	US	150,679	1	1	1	1	1	0	0	0	0	0	0	1	0	0	0	**6**
9	Key Bank	US	88,961	1	1	1	1	0	0	1	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	0	**7**
Panel B: Canadian Banks																			
1	Royal Bank of Canada (43)	CAN	398,981	1	1	1	1	1	1	1	0	2	1	0	1	1	1	0	**13**
2	Toronto Dominion Bank	CAN	310,379	1	1	0	0	0	0	0	0	2	0	0	0	0	0	0	**4**
3	Scotiabank	CAN	266,879	1	1	1	1	1	1	1	0	2	0	0	1	1	2	0	**13**
4	Bank of Montreal	CAN	252,862	1	1	1	1	1	1	1	0	2	1	0	1	1	2	0	**14**
5	CIBC (a)	CAN	238,277	1	1	1	1	1	1	1	0	2	1	0	1	1	2	0	**14**
6	National Bank of Canada	CAN	91,444	1	1	1	1	1	1	1	0	2	1	0	0	2	1	1	**14**
Panel C: International Banks																			
1	Barclay PLC	UK	1,586,879	1	1	1	1	1	1	1	0	2	0	0	1	0	2	0	**12**
2	UBS AG	SWI	1,563,282	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	**4**
3	BNP Paribas SA	FRA	1,483,934	1	1	1	1	1	1	0	0	2	0	0	0	2	2	0	**12**
4	Royal Bank of Scotland	UK	1,300,124	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	**8**
5	Credit Agricole SA	FRA	1,251,997	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	**7**
6	Deutsche Bank AG	GER	1,170,277	1	1	1	1	1	1	1	0	2	1	0	1	1	1	1	**14**
8	ABN AMRO Holding NV	NED	1,038,929	1	1	1	1	1	1	1	0	2	1	0	0	2	2	0	**14**
9	Credit Suisse Group	SWI	1,016,050	1	1	1	1	1	1	1	0	2	0	0	1	1	2	0	**13**
11	Société Générale	FRA	1,000,728	1	1	1	1	1	1	1	0	2	0	0	0	2	2	0	**13**
12	ING Bank NV	NET	983,764	1	1	1	1	1	1	1	0	2	1	1	0	0	2	0	**13**
13	Banco Santander Central	SPA	954,361	1	1	1	1	1	1	0	1	1	1	0	0	2	2	0	**13**
14	UniCredito Italiano SpA	ITA	928,285	1	1	0	1	1	1	1	0	0	1	0	0	0	2	0	**9**
15	Sumitomo Mitsui Banking	JAP	916,710	1	1	1	1	0	0	0	0	0	0	0	0	0	2	0	**6**

16	Bank of Tokyo-Mitsubishi	JAP	865,663	1	1	1	1	1	1	1	0	0	0	0	0	0	2	0	**9**
17	Caisse Nationale d. Caisses	FRA	739,311	1	1	1	1	1	1	0	0	0	0	0	0	0	2	0	**8**
19	Fortis Bank NV/SA	BEL	700,515	1	1	1	1	1	1	1	0	2	0	0	0	0	1	0	**10**
20	Ind.&Com. Bank of China	CHN	675,395	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
21	HSBC plc	UK	663,385	1	1	1	1	1	1	1	0	0	0	0	1	0	0	0	**8**
22	Mizuho Bank Ltd	JAP	663,014	1	1	1	1	0	0	1	0	2	0	0	0	0	2	0	**9**
23	Rabobank Nederland	NED	597,115	1	1	1	1	1	1	0	0	2	0	0	0	0	0	0	**8**
24	Agriculture Bank of China	CHN	591,190	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
26	The Norinchukin Bank	JAP	582,567	1	1	0	0	0	0	0	0	0	0	0	0	0	2	0	**4**
27	Bayerische Hypo-und Ver.	GER	582,122	1	1	0	1	1	1	1	0	2	1	0	0	2	2	0	**13**
28	Calyon	FRA	567,724	1	1	0	1	1	0	0	0	2	0	0	0	0	0	0	**6**
29	Dresdner Bank Group	GER	544,199	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
30	Lloyds TSB Group plc	UK	531,767	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	**6**
32	Commerzbank AG	GER	524,724	1	1	1	1	1	0	1	0	2	0	0	0	0	0	0	**8**
33	Bank of China Ltd	CHN	515,972	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
34	Landesbank Baden-Wurtte.	GER	477,606	1	1	1	1	1	0	1	0	2	0	0	0	2	1	0	**11**
35	DZ Bank AG (b)	GER	473,730	1	1	1	1	0	0	1	0	2	0	0	0	0	0	0	**7**
37	China Construction Bank	CHN	471,792	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
38	Banco Bilbao Vizcaya Arg.	SPA	462,833	1	1	1	1	1	1	0	1	1	0	0	0	2	2	0	**12**
41	Bayerische Landesbank	GER	402,046	1	0	1	1	1	1	1	0	0	0	0	0	0	2	0	**8**
42	Kreditanstalt fur Wiederau.	GER	401,411	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
44	Danske Bank A/S	DEN	384,604	1	1	1	1	1	1	1	0	0	1	0	0	0	0	0	**8**
45	Nordea Group	SWE	383,993	1	1	1	1	1	1	1	0	2	1	0	0	2	2	0	**14**
47	Banque Federative du CM	FRA	352,516	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**
48	HSBC HK (c)	HK	344,687	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	**6**
49	Banca Intesa SpA	ITA	322,641	1	1	0	0	0	0	0	0	2	0	1	0	2	2	0	**9**
50	National Australia Bank	AUS	320,418	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	**7**

Notes: Panel A presents for each of the ten largest US commercial banks (in assets) the domestic rank and, when applicable, the rank in the world Top 50 (in parentheses), the assets in million of US dollars, the bank's score on each item entering into the calculation of the VaR Disclosure Index (VaRDI), and the firm's VaRDI for the year 2005. Panel B presents similar information for the six largest Canadian commercial banks and Panel C for the fifty largest international commercial banks. US and Canadian banks included in the world Top 50 are not included in Panel C. Banks' assets are as of December 31, 2005 and were collected from the Board of Governors of the Federal Reserve System website for US banks, banks' annual reports for Canadian banks, and Bankersalmanac.com for international banks. VaR disclosure scores have been allocated according to annual 10-K forms (downloaded from the SEC-EDGAR website) and annual reports for US banks and annual reports for Canadian (from the SEDAR website) and international banks (from the firms' websites). 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) 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 display the results for four Top 50 banks that do not have an annual report for the year 2005: Bank of Scotland #25, UK, assets: 586,543 (part of the Royal Bank of Scotland #4), Mizuho Corporate Bank Ltd #31, JAP, assets: 526,193 (part of Mizuho Bank #22), National Westminster Bank #39, UK, assets: 447,387 (part of HBOS plc which is not in the Top 50), and Abbey National plc #46, UK, assets: 355,423 (part of Banco Santander #13). (a) The full name is Canadian Imperial Bank of Commerce, (b) DZ Bank AG Deutsche Zentral-Genossenschaftsbank, and (c) Hongkong and Shanghai Banking Corp.

Table III: VaR Disclosure by Country

	world	US	GER	UK	CAN	FRA	JAP	CHN	NED	ITA	SPA	SWI
Number of Banks	60	10	8	7	6	6	5	4	3	2	2	2
Average VaRDI	8.1	7.0	7.9	8.5	12.0	8.0	7.0	0.0	11.7	9.0	12.5	8.5
Standard Deviation VaRDI	4.4	3.7	4.9	2.5	3.9	4.0	2.4	0.0	3.2	0.0	0.7	6.4
Minimum VaRDI	0	2	0	6	4	2	4	0	8	9	12	4
Maximum VaRDI	14	13	14	12	14	13	9	0	14	9	13	13
Holding Period	89	90	88	100	100	100	100	0	100	100	100	100
Confidence Level	89	100	75	100	100	100	100	0	100	100	100	100
High, Low, Average VaR	71	80	63	100	83	67	75	0	100	0	100	50
Year-End VaR	79	80	75	100	83	83	75	0	100	50	100	100
Risk Category	68	60	63	100	83	83	25	0	100	50	100	50
Diversification	55	40	38	75	83	67	25	0	100	50	100	50
Previous Year	63	60	75	100	83	33	50	0	67	50	0	100
Histogram Daily VaR	4	0	0	0	0	0	0	0	0	0	100	0
Plot Daily VaR	48	20	63	25	100	50	25	0	100	50	100	50
Hypothetical Trading Revenue	21	0	25	0	67	0	0	0	67	50	50	0
No Trading Fees	4	0	0	0	0	0	0	0	33	50	0	0
Histogram Daily Trading Revenue	25	50	13	75	67	0	0	0	0	0	0	50
Plot Daily Trading Revenue	32	20	38	0	83	33	0	0	33	50	100	50
Exceptions	54	40	50	25	83	50	100	0	67	100	100	50
Explanation of Exceptions	4	0	13	0	17	0	0	0	0	0	0	0

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) 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.

Table IV: Summary Statistics

	Bank of America	Credit Suisse First Boston	Deutsche Bank	Royal Bank of Canada	Société Générale
Panel A: Trading Revenue					
Mean	13.85	5.03	41.48	5.44	9.85
Variance	222.24	369.16	509.90	8.69	102.51
Skewness	0.123	0.240*	0.380*	0.457*	0.717*
Kurtosis	4.93*	9.90*	4.42*	4.19*	5.50*
Bera-Jarque Test	159.11*	1,510.30*	83.58*	93.27*	268.94*
Autocorrelation	0.064	0.124	0.423	0.099	0.119
ADF	-31.09*	-40.63*	-30.00*	-44.21*	-36.48*
LB-12	9.38	66.20*	417.12*	63.30*	22.86*
ARCH-12	23.73*	44.99*	92.42*	32.32*	7.51
Minimum	-57.39	-105.30	-39.92	-2.99	-18.56
Maximum	84.33	138.45	145.23	18.41	65.32
Panel B: Value-at-Risk					
Mean	43.43	63.55	49.82	11.30	29.58
Variance	144.14	215.89	253.94	7.85	38.67
Skewness	0.10	0.02	0.91	1.40	1.11
Kurtosis	2.81	2.29	2.73	5.46	4.71
Bera-Jarque Test	3.05	21.94	138.14	579.59	254.20
Autocorrelation	0.892	0.947	0.977	0.907	0.937
ADF	-9.45*	-9.53*	-7.57*	-12.02*	-7.62*
LB-12	7,246.70	8,563.80	10,154.00	7,242.70	4,590.10
ARCH-12	2,916.90	4,350.40	7,932.30	5,998.90	2,338.60
Minimum	11.38	27.16	26.18	6.54	17.86
Maximum	90.49	100.19	99.09	23.12	54.44
VaR Method	Historical Simulation	Historical Simulation	Monte Carlo Simulation	Historical Simulation	Historical Simulation
Panel C: Backtesting Value-at-Risk					
Number Trading Days	1,008	1,031	989	998	776
Expected Exceptions	10	10	10	10	8
Actual Exceptions	4	6	0	0	0
LR Coverage Test	4.803	2.142	19.880	20.061	15.598
p-value	(0.028)	(0.143)	(0.000)	(0.000)	(0.000)

Notes: This table presents for each sample bank some summary statistics for the trading revenues (Panel A) and Value-at-Risk measured in absolute values (Panel B) for the five sample banks, and backtests of VaR (Panel C). Data are expressed in local currency and the sample period is 2001-2004 for all banks, except for Société Générale which sample covers 2002-2004. The summary statistics include the first four moments, minimum, and maximum of each variable, the Bera-Jarque normality test, the first-order autocorrelation coefficient, the Augmented Dickey-Fuller test (ADF), the Ljung-Box (LB) autocorrelation test using 12 lags, and the ARCH-12 test, which is a LB test applied to the squared demeaned returns. The ADF test includes an intercept, time trend and twelve lags. * denotes significant at the 5% confidence level.

Table V: GARCH Models of Daily Trading Revenues

	Bank of America		**Credit Suisse First Boston**		**Deutsche Bank**		**Royal Bank of Canada**		**Société Générale**	
	GARCH	X-GARCH	GARCH	X-GARCH	GARCH	X-GARCH	GARCH	X-GARCH	GARCH	X-GARCH
μ	13.709**	13.667**	5.267**	5.152**	21.431**	21.806**	5.354**	5.354**	9.470**	9.471**
	(0.4343)	(0.4364)	(0.5246)	(0.4961)	(1.3721)	(1.3805)	(0.0895)	(0.0895)	(0.4270)	(0.3403)
ρ	-	-	-	-	0.4743**	0.4759**	-	-	-	-
					(0.0313)	(0.0317)				
ω	15.408*	13.435	48.045	13.985	226.550**	86.930	2.781*	2.861	19.277**	36.084**
	(9.0837)	(8.6099)	(89.058)	(15.308)	(54.830)	(77.851)	(1.435)	(1.514)	(2.679)	(6.464)
α	0.0468*	0.0455*	0.1387	0.0933	0.2491**	0.1928**	0.1317*	0.1310**	0.0254	0.0264
	(0.0223)	(0.0227)	(0.1622)	(0.0574)	(0.0645)	(0.0572)	(0.0525)	(0.0526)	(0.0284)	(0.0352)
β	0.8849**	0.8828**	0.7384	0.8191**	0.2566*	0.1421	0.5532**	0.5542**	0.7854**	0.5562**
	(0.0542)	(0.0565)	(0.3869)	(0.1196)	(0.1334)	(0.2306)	(0.1962)	(0.1974)	(0.0476)	(0.0222)
γ	-	0.0013	-	0.0046	-	0.0786**	-	-0.0006	-	0.0071
		(0.0016)		(0.0034)		(0.0227)		(0.0025)		(0.0078)
ν	0.1563**	0.1545**	0.2142**	0.2141**	0.2119**	0.1986**	0.1249**	0.1250**	0.1535**	0.1550**
	(0.0297)	(0.0298)	(0.0279)	(0.0308)	(0.0344)	(0.0324)	(0.0291)	(0.0291)	(0.0345)	(0.0332)
LL	**-4,118.8**	**-4,118.4**	**-4,407.5**	**-4,404.1**	**-4,329.4**	**-4,311.2**	**-2,469.2**	**-2,469.2**	**-2,874.8**	**-2,874.6**

Notes: This table displays the coefficient estimates and robust standard error (in parentheses) for different GARCH models estimated over the sample period 2001-2004, expect for Société Générale which covers 2002-2004. Revenues are modeled as $y_{t+1} = \mu + \rho \cdot y_{t+1} + \sqrt{h_{t+1|t}}\, z_{t+1}$ where $h_{t+1|t} = \omega + \alpha \cdot e_t^2 + \beta \cdot h_{t|t-1} + \gamma \cdot VaR_{t+1|t}$ and z is a standardized T random variable with ν^{-1} degrees of freedom. The γ coefficient is fixed to zero in the GARCH specification and it is estimated as a free parameter in the augmented GARCH (X-GARCH) specification. * (**) denotes a coefficient estimate significant at the 5% (1%) confidence level.

Table VI: Forecasting Trading Revenue Volatility

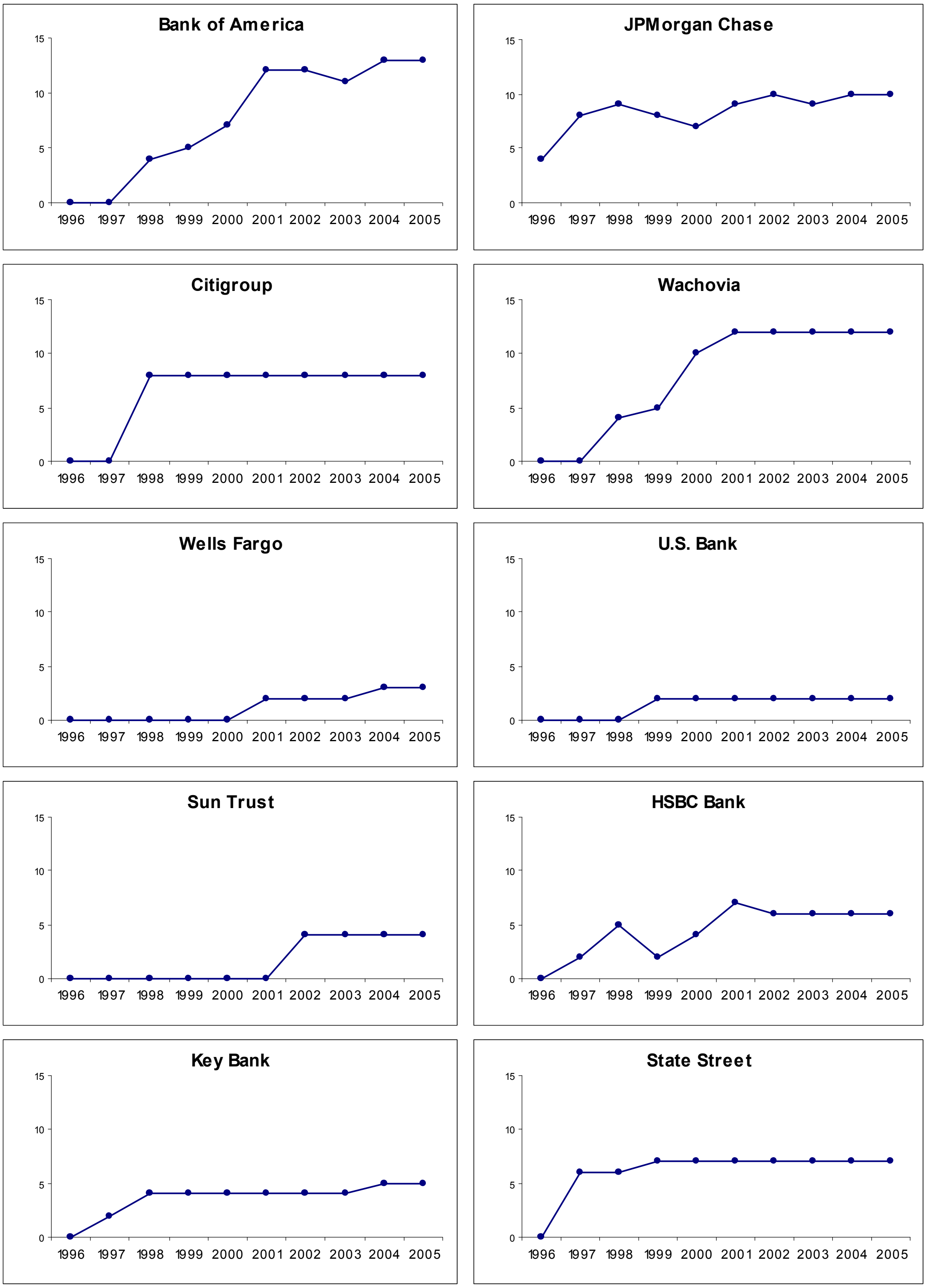
	Bank of America			Credit Suisse First Boston			Deutsche Bank			Royal Bank of Canada			Société Générale		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
a	317.98**	256.94**	218.63**	237.83**	225.75**	174.22**	1741.80**	1779.10**	1676.50**	42.61**	26.93**	30.77**	274.93**	331.63**	389.91**
	(44.39)	(70.35)	(74.94)	(58.92)	(43.42)	(64.92)	(145.40)	(108.97)	(156.72)	(2.98)	(3.90)	(4.69)	(43.74)	(90.09)	(100.56)
b	0.040	-	0.033	0.020	-	0.015	0.044	-	0.036	-0.027	-	-0.026	-0.063	-	-0.066
	(0.022)		(0.022)	(0.014)		(0.014)	(0.039)		(0.040)	(0.018)		(0.018)	(0.051)		(0.051)
c	-	0.582*	0.496	-	0.232*	0.215*	-	0.189	0.166	-	1.334**	1.330**	-	-1.098	-1.158
		(0.296)	(0.302)		(0.092)	(0.093)		(0.147)	(0.149)		(0.409)	(0.409)		(0.912)	(0.912)
R^2	**0.004**	**0.005**	**0.008**	**0.003**	**0.008**	**0.010**	**0.002**	**0.002**	**0.003**	**0.003**	**0.014**	**0.017**	**0.003**	**0.003**	**0.006**

Notes: This table presents the coefficient estimates, robust standard errors (in parentheses), and R-squared for several volatility regressions. We regress the squared trading revenues on two volatility forecasts: the square of the value-at-risk disclosed by the bank and an out-of-sample GARCH-T forecast of the conditional variance of the trading revenues:

$$R_{t+1}^2 = a + b \cdot VaR_{t+1|t}^2 + c \cdot h_{t+1|t} + u_{t+1}$$

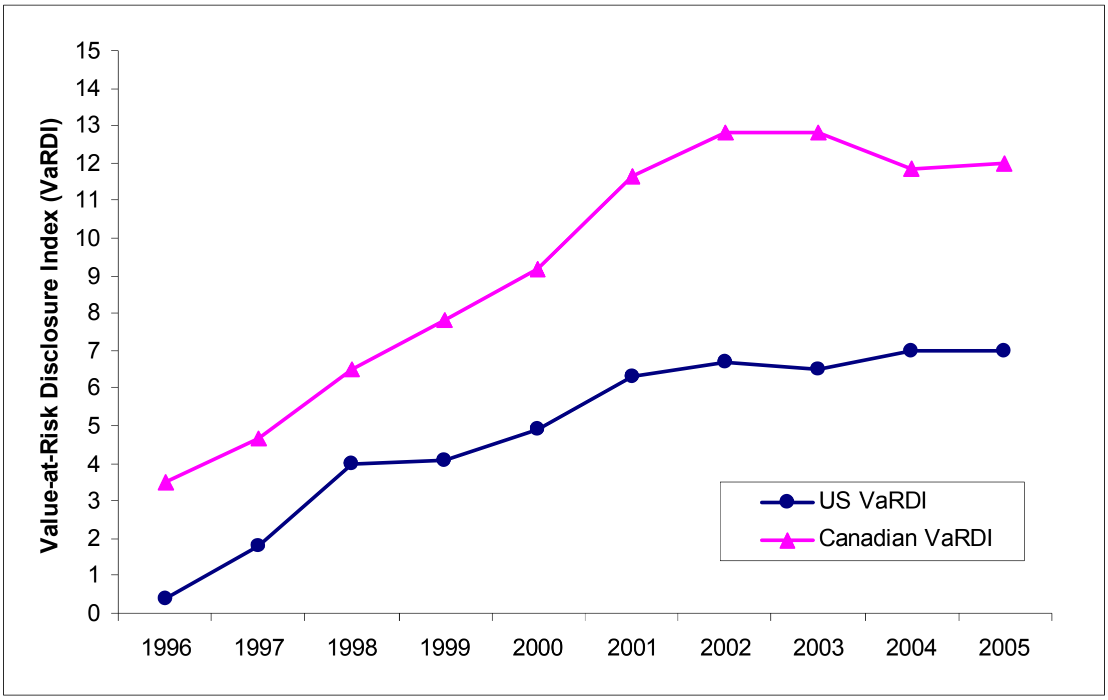
* (**) denotes a coefficient estimate significant at the 5% (1%) confidence level.

Figure 1: VaR Disclosure Index for the Top 10 US Banks



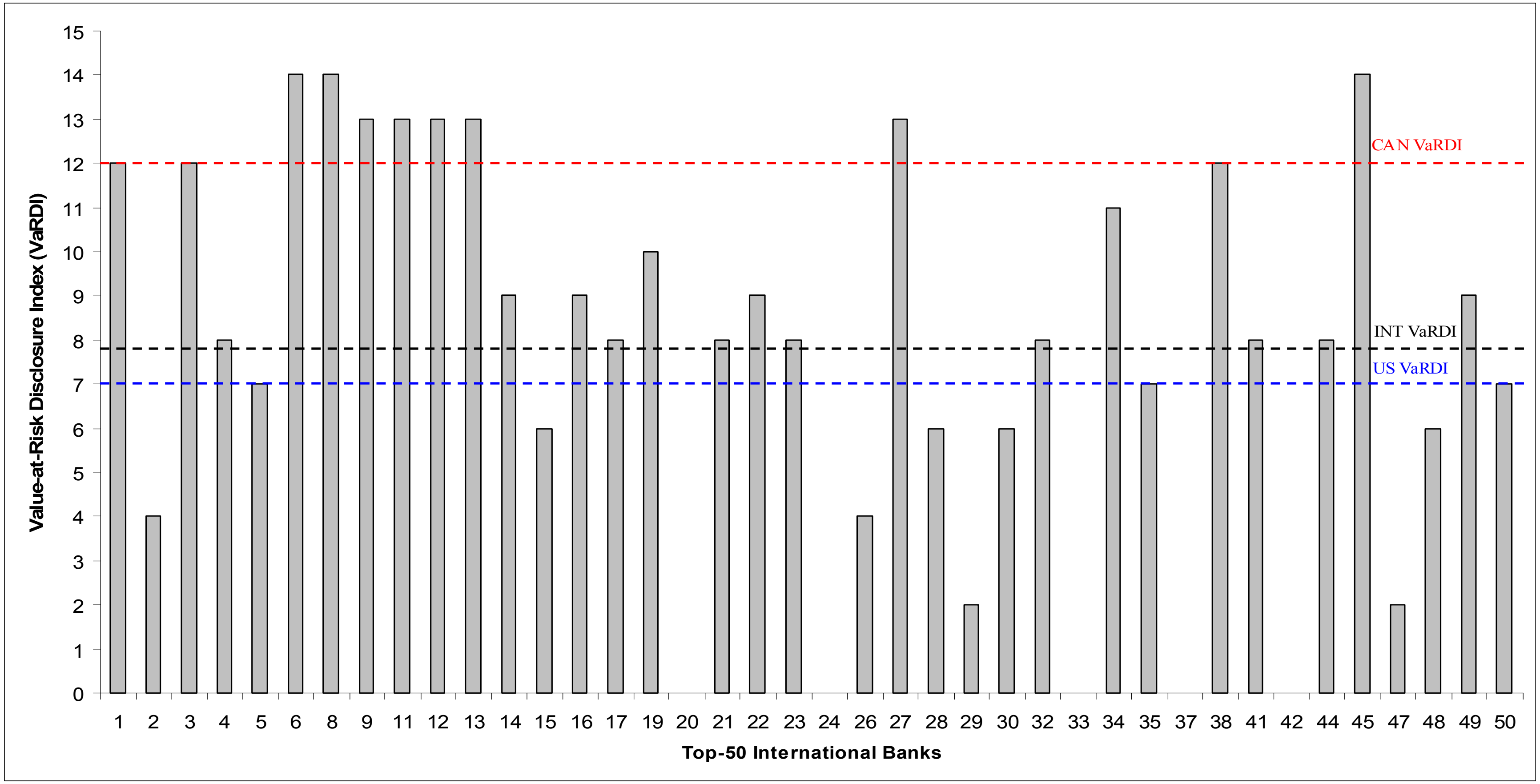
Notes: This figure plots the VaR Disclosure Index (VaRDI) computed for each of the ten largest US commercial banks between 1996 and 2005.

Figure 2: VaR Disclosure Index in the US and in Canada



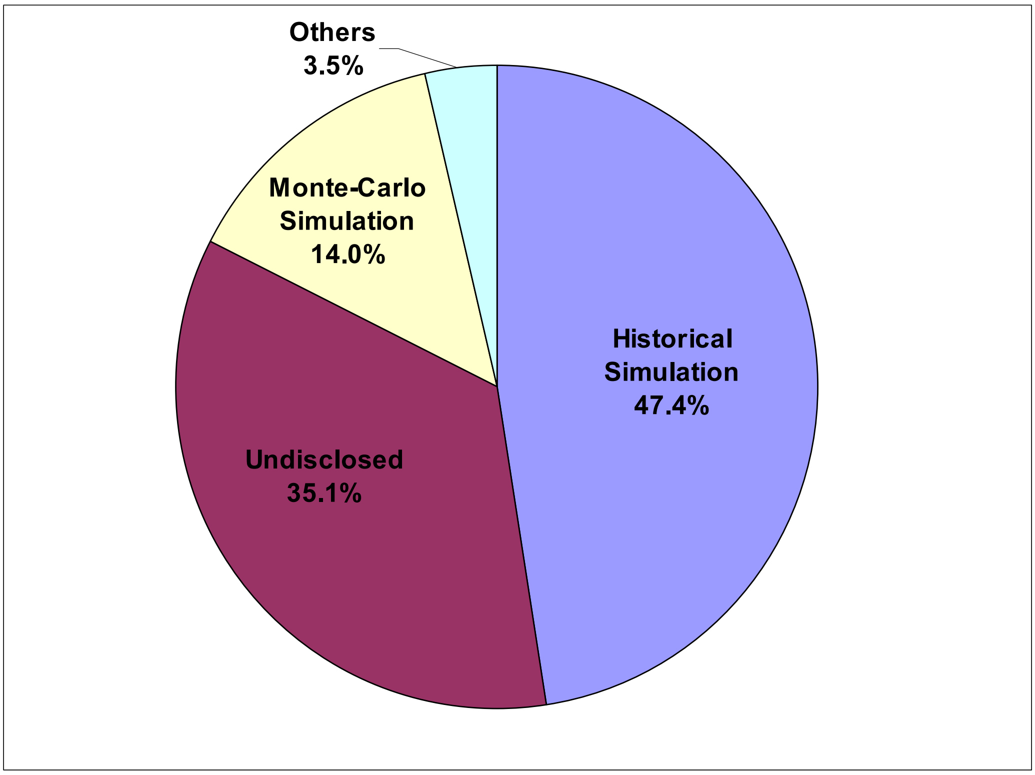
Notes: This figure plots the average VaR Disclosure Index (VaRDI) computed for (1) the ten largest US commercial banks and (2) the six largest Canadian commercial banks between 1996 and 2005.

Figure 3: VaR Disclosure Index in the World



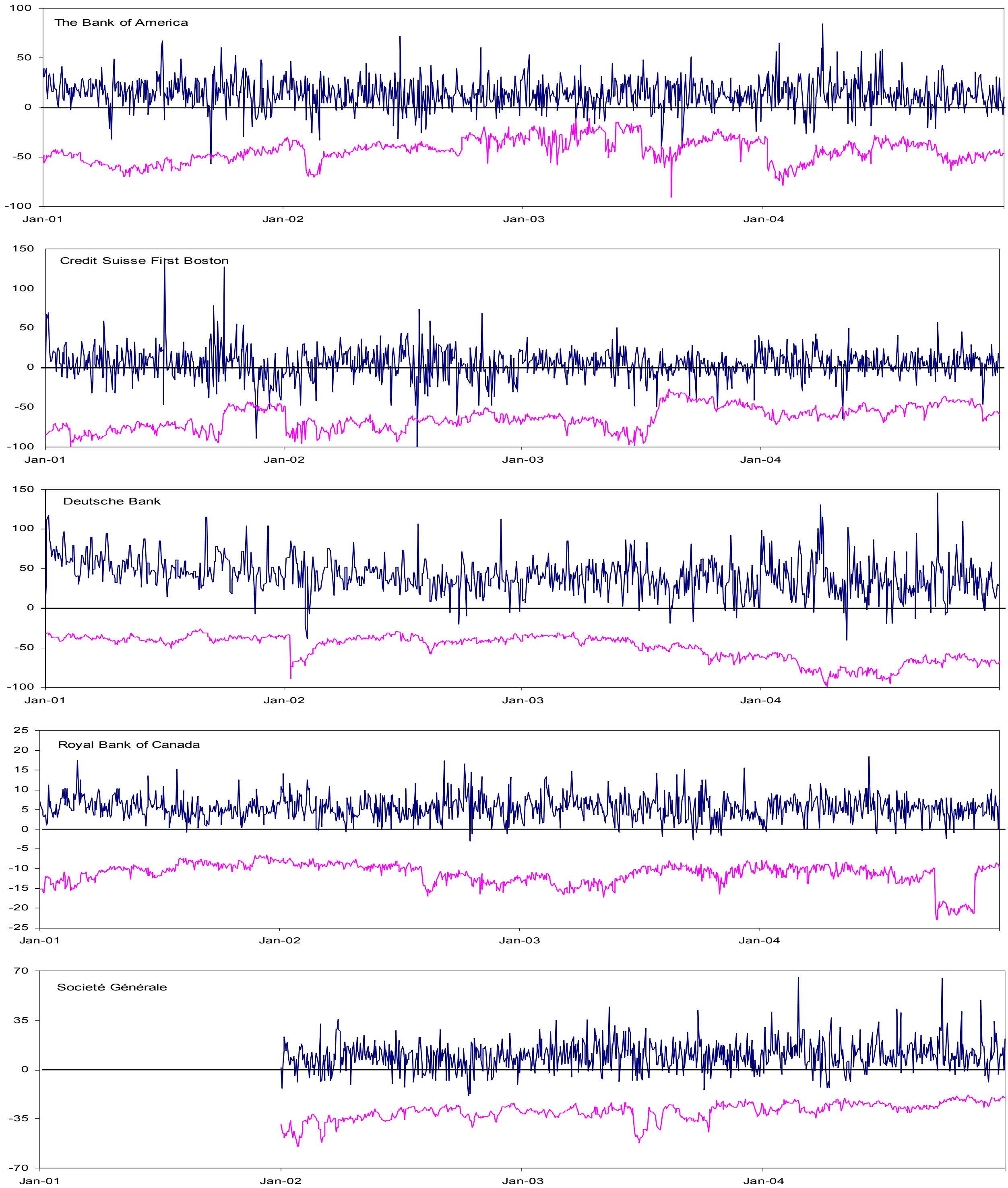
Notes: This figure plots (1) the value of the 2005 VaR Disclosure Index (VaRDI) for each non-US, non-Canadian commercial banks included in the world Top 50 (vertical bars), (2) the average 2005 VaRDI (dotted horizontal lines) computed for the ten largest US commercial banks (US VaRDI = 7.0), the six largest Canadian commercial banks (CAN VaRDI = 12.0), and all non-US, non-Canadian commercial banks included in the world Top 50 (INT VaRDI = 7.8). The VaRDI for banks ranked #25, #31, #39, and #46 are not available (see caption of Table 2 for details).

Figure 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.

Figure 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 million and are expressed in local currencies.

Appendix: Data Extraction Method

Since actual VaR and trading revenues are not publicly available in a machine-readable format, we extract the data from the graphs included in annual reports by following the following steps.

[1] Convert the original graph from the annual report (available as a PDF file) into a JPG file.

[2] Import the JPG file into MATLAB and define it as an image called, for instance, *im*.

```
Command: im = imread('name.jpg')
```

[3] Display the image in MATLAB.

```
Command: image(im)
```

[4] Convert the graph scale into a MATLAB scale. For instance, the zero value on the vertical axis of the graph corresponds to a value of 100 in MATLAB, 10 corresponds to 80, 20 corresponds to 60, etc. This implies a conversion scale factor of $s = 2 = (100 - 80) / (10 - 0) = (80 - 60) / (20 - 10)$.

[5] Add vertical lines on the image (Edit, Axes Properties, Show Grid, and manually enter the coordinates where the lines have to be in 'Ticks'). The horizontal distance d between two adjacent lines is defined using two successive clear-cut data points. Find the coordinate value on the horizontal axis for the first and last data point, which we call f and l. The number of vertical lines is $(l - f) / d$ and the number of observations is $1 + (l - f) / d$. Note that the fact that the exact number of data points is not required to be known is a key advantage of our data extraction algorithm.

[6] Zoom in and click on each data point. By doing so, we capture the two-dimensional coordinates of each data point.

Command: data = ginput(*n*)

where n is the number of data points to be extracted. Then, sequentially click on the data points. The 2-D coordinates are automatically stored into the ($n \times 2$) *data* matrix.

[7] Convert the MATLAB vertical coordinates (second column of the *data* matrix) into graph coordinates. For each data point, compute (*zero coordinate value* - *point coordinate value*) / s.

As a refinement, we can plot the extracted data in EXCEL and superimpose the graph of the extracted data with the original graph. This can be done by right clicking on the graph of the extracted data and Format Chart Area / Area: none and Format Plot Area / Area: none. If necessary, we can manually adjust the extracted series until reaching a perfect match between the two lines.

We first gauge the accuracy of our data extraction method using real data for which exact numeric values are readily available in standard databases. Specifically, we use daily, weekly, and monthly data on the S&P composite index returns for the year 2005. The use of different frequencies allows us to investigate how the extraction method performs when the dataset grows large (from 12 monthly observations to 252 daily observations). We consider different types of graphs, i.e., lines, lines with markers, and bars. The experiment protocol is as follows. We sequentially provide our research assistant with a pdf file containing graphs based on line, line plus markets, and bars (see Figure A1). After our research assistant had extracted the data from the line graph, we gave him a pdf file containing the line with markers, and after receiving the data we submitted the pdf file for the bars. In the first part of the experiment the research assistant applies the first seven steps of the algorithm. The research assistant is given no information about the data. In particular, he does not know the number of data points in each graph or the initial and terminal value of the time-series. Note that in real applications, the final value (e.g. year end) of the series is often known.

We present the results in Panel A of Table AI. For each graph, we report the time required to extract the data, the extraction error (measured by the mean absolute error / mean absolute return), and the error variance ratio (variance of the error / variance of the true return). We reach several conclusions. Firstly, the necessary time to extract data from a simple line is longer than with other types of graphs. When the sample size is increased twenty-one times (from 12 to 252 observations), the extraction time is increased by a factor of six or nine depending on the type of graph. Secondly, regardless of the type of graph and the sample size, our data extraction algorithm leads systematically to the exact number of data points. Thirdly, the accuracy slightly deteriorates with sample size. The extraction error remains below 1% for marker-based and bar graphs, and is in excess of 2% for a line-based graph based on one year of daily data. The ratio of the variance of the extraction error and the variance of the true data is remarkably small. Furthermore, it is important to keep in mind that these accuracy figures are based on the first seven steps of the data extraction algorithm only, and that accuracy can be improved using the final refinement step. After superimposing the original graph and the graph of the extracted data, and slightly adjusting the extracted data, the extraction error for the 252 data-point line graph drops to 1.12%.

We simulate a second data set that consists of hypothetical trading revenues and VaRs. We generate the two artificial time series using the following GARCH process.

$$y_{t+1} = 14 + e_{t+1} \quad \text{(A1)}$$

$$h_{t+1|t} = 14 + 0.05 \cdot e_t^2 + 0.85 \cdot h_{t|t-1} \quad \text{(A2)}$$

where $e_{t+1} = \sqrt{h_{t+1|t}}\, z_{t+1}$ and z_{t+1} follows a standardized T distribution with $6.6667 = 1/0.15$ degrees of freedom. The VaR for a conditionally T(6.6667) process is given by $VaR_{t+1|t} = 14 - 2.5436\sqrt{h_{t+1|t}}$ where -2.5436 is the 1st percentile of a T distribution with 6.6667 degrees of freedom multiplied by $\sqrt{4.6667/6.6667}$ to standardize it (since the variance of a $T(\nu)$ random variable is $\nu/(\nu-2)$). We use this model to simulate the data since it accurately models the volatility of actual trading revenues. In this simulation, the parameters have been calibrated using the actual data of Bank of America. We plot the data using a single line without markers (see Figure A2) and we implement the same protocol as for actual stock returns. We present the results in Panels B and C of Table AI. We find that the extraction process is remarkably accurate leading to an extraction error of 1.76% for trading revenues and 1.35% for VaR figures, with small error variance ratios.

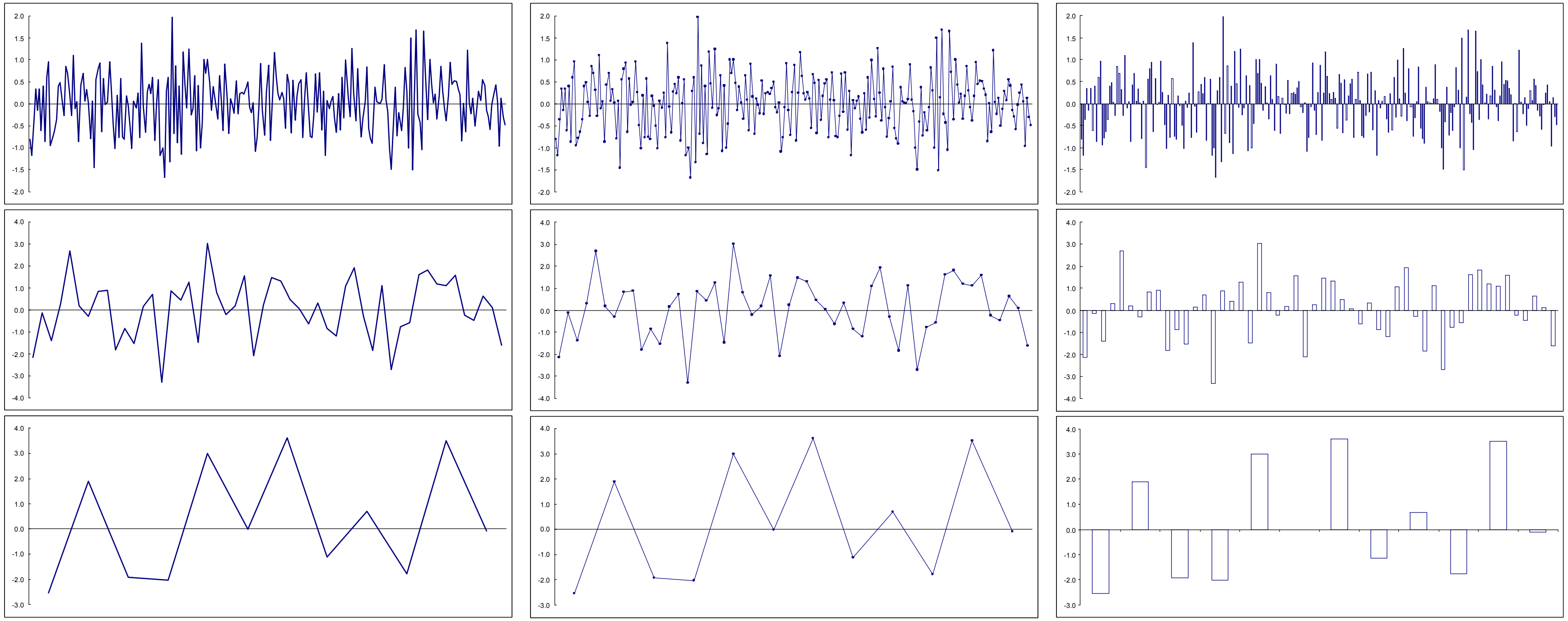
As a final check, we fit a GARCH model separately to the true and extracted time series to gauge the impact of the extraction error on the parameter estimates. We consider actual daily stock index returns (Panel A, 252 observations) and simulated daily trading revenues (Panel B, 252 observations). We find that the parameter estimates based on true and extracted data are not materially different, i.e., they are equal to at least two decimals. Furthermore, the effect of using extracted data instead of true data is a change of 2 to 5% of the parameter standard errors.

Table AI: Controlled Experiment

		Graph Type:			Graph Type:			Graph Type:		
		Extraction Time	Extraction Error	Error Variance Ratio	Extraction Time	Extraction Error	Error Variance Ratio	Extraction Time	Extraction Error	Error Variance Ratio
Panel A: Actual Stock Returns										
Daily	252	180 min	2.87%	0.148%	90 min	0.95%	0.007%	90 min	0.99%	0.010%
Weekly	52	60 min	1.39%	0.024%	30 min	0.65%	0.004%	30 min	0.71%	0.005%
Monthly	12	15 min	0.41%	0.002%	15 min	0.57%	0.000%	15 min	0.68%	0.004%
Panel B: Simulated Trading Revenues										
Daily	252	180 min	1.76%	0.275%	-	-	-	-	-	-
Panel C: Simulated Value-at-Risk										
Daily	252	180 min	1.35%	0.192%	-	-	-	-	-	-

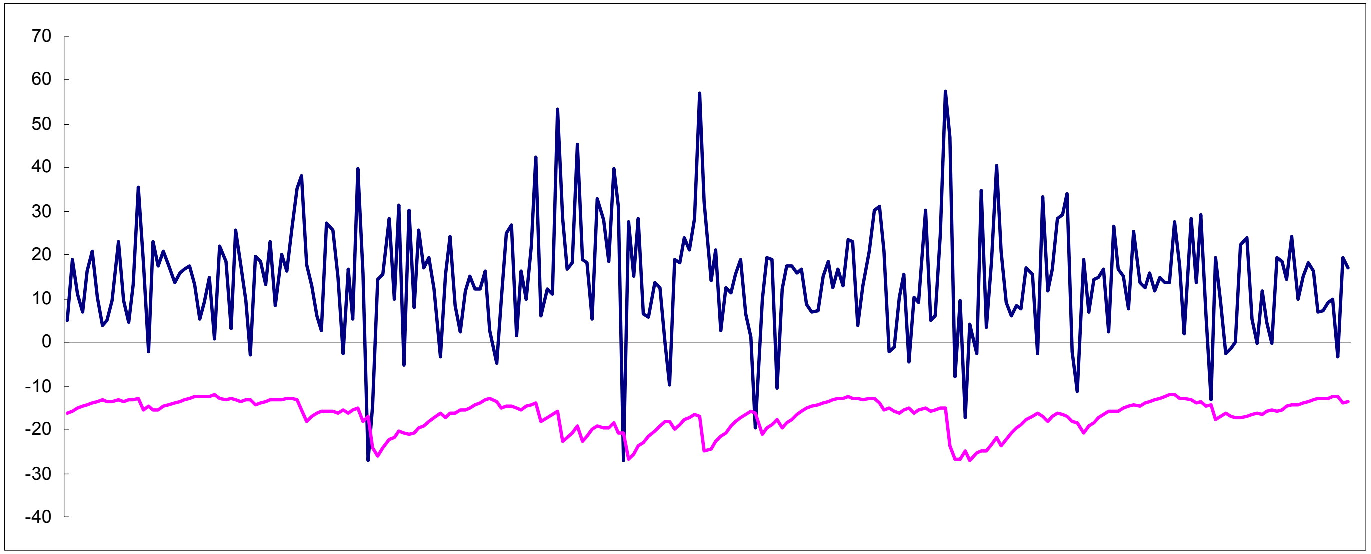
Notes: This table presents the results of a controlled experiment based on real and simulated data. In Panel A, we use our data extraction algorithm to extract data from several graphs displaying actual daily (252 observations), weekly (52 observations), and monthly (12 observations) returns on the S&P Composite Stock Index for the year 2005 (source: CRSP). We use different types of graphs, namely line, line with marker, and vertical bars (see Figure A1). For each graph, we report the elapsed extraction time, the extraction error (mean absolute error / mean absolute return), and the error variance ratio (variance of the error / variance of the true return). In Panels B and C, we repeat the same analysis using artificial daily trading revenues and Value-at-Risk (see Figure A2).

Figure A1: Actual Stock Index Returns



Notes: This figure presents the nine graphs in Panel A of Table AI. The top graphs display 252 daily returns on the S&P Composite stock index, the middle graphs display 52 weekly returns on the S&P Composite stock index, and the bottom graphs display 12 monthly returns on the S&P Composite stock index. The data has been extracted from the CRSP database. To save space, the graphs have been reduced by a 1/3 ratio.

Figure A2: Simulated Value-at-Risk and Trading Revenues



Notes: This figure displays a simulated time-series of 252 VaRs (lower line) and trading revenues (upper line). Trading revenues have been generated using a T distribution:

$$y_{t+1} = 14 + e_{t+1}$$

and VaRs are based on a GARCH model:

$$h_{t+1|t} = 14 + 0.05 \cdot e_t^2 + 0.85 \cdot h_{t|t-1}$$

where $e_{t+1} = \sqrt{h_{t+1|t}}\, z_{t+1}$ and z_{t+1} follows a standardized T distribution with $6.6667 = 1/0.15$ degrees of freedom. The VaR for a conditionally T(6.6667) process is given by $VaR_{t+1|t} = 14 - 2.5436\sqrt{h_{t+1|t}}$ where -2.5436 is the 1st percentile of a T distribution with 6.6667 degrees of freedom multiplied by $\sqrt{4.6667/6.6667}$ to standardize it (since the variance of a $T(\nu)$ random variable is $\nu/(\nu-2)$).