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CHAPTER 6

Operational Risk and Stock Market Returns: Evidence from Turkey

M. Nihat Solakoğlu and K. Ahmet Köse

ABSTRACT

Following several high-severity, low-frequency events in the financial sector, operational risk has gained importance both for regulators and managers of financial sector firms during the last decade. The banking sector in Turkey also experienced a severe crisis, due not only to economic conditions but also to events directly related to operational risk. However, it was only by mid-2007 that banks in Turkey were required to have necessary capital for operational risk. This study investigates the banking sector in Turkey in relation to operational risk. In addition, the study analyzes the reaction of stock market return to operational risk events between 1998 and 2007 using event study analysis. We find that returns show a negative reaction starting right before the event date. Moreover, this negative reaction appears to be significant for pre-2002 events but not for events after 2002.

6.1 INTRODUCTION

For risk management departments in financial institutions, four types of risks need to be managed to minimize the loss of a portfolio or even the firm itself. These risk types are market risk, credit risk, liquidity risk, and operational risk. Market risk is created by the unexpected changes in market prices. Credit risk is the risk financial institutions face when there is a complete or partial loss related to default. Liquidity risk exists if there is a possibility that an asset or a position in a portfolio cannot be converted quickly to liquid assets or the conversion occurs quickly but at a lower price than fair market price (Jarrow 2008).

Operational risk is not new for financial institutions; they face many such losses in the past. However, the focus on the management of operational risk, by institutions and regulatory agencies, has increased recently following highly publicized and costly operational losses in the financial sector. Some examples of these costly losses are: the loss of about $1.3 billion due to a rogue trader, which led the Barings bank to bankruptcy in 1995; a $2 billion settlement paid by Prudential Insurance in 1990s; the $1.2 billion payment to auto insurance policyholders by State Farm Insurance because of a breach-of-contract lawsuit (see Cummins et al. 2006). A more current example is the loss of about $7.2 billion due to unauthorized derivatives trading in January 2008[1] at Société Générale. This is the largest operational loss event so far caused by a rogue trader. Along with high cost and publicity of operational losses, higher financial transparency and complex production technologies used in the financial sector have contributed to increasing attention on the management of operational risk (Cummins et al. 2006).[2]

Operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" by the revised Basel Committee report (Basel Committee [BCBS] 2006, 144). Legal risk in the definition includes "exposure to fines, penalties, or punitive damages resulting from supervisory actions, as well as private settlements." As clear from the definitions, institutions can face operational risk because of internal or external events. The other three types of risks—market, credit, and liquidity risks—occur only under specific external events. Furthermore, operational risk is asymmetric. That is, institutions do not expect any gains but face loss of a portfolio or the firm under an operational risk event (Cummins et al. 2006).[3]

The Basel Committee breaks operational losses into eight standard business lines for banks and seven event types. The business lines are:

1. Corporate finance
2. Trading and sales
3. Retail banking
4. Commercial banking
5. Payment and settlement
6. Agency services
7. Asset management
8. Retail brokerage

Operational losses can be caused by any of these event types:

1. Employment practices and workplace safety
2. Internal fraud
3. External fraud
4. Clients, products, and business practices
5. Damage to physical assets
6. Business disruption and system failures
7. Execution, delivery and process management (BCBS 2006)

The work on operational risk mostly concentrates on the estimation of operational risk processes and the determination of the economic capital (Jarrow 2008). Empirical works have paid little attention to modeling of operational risk, which caused banks to allocate operational risk capital via a top-down approach. One reason was the lack of operational loss data. Several vendors, such as OpRisk and OpVantage, have constructed databases recently using mostly public information. Another reason is the availability of the information; not all operational losses are publicly reported (Fontnouvelle et al. 2003).

It appears that operational losses are concentrated in retail and commercial banking and retail brokerage mostly within the United States. For losses outside the United States, retail brokerage seems to have a lower weight, but retail and commercial banking still has the lead. Furthermore, while "clients, products, and business practices" is the leading event, followed by internal and external fraud events, within the United States, the internal fraud event is the leading cause of operational losses outside the United States (Fontnouvelle et al. 2003).[4]

Given the importance of operational risk in the financial sector and the role it played on Turkish banks in the 2001 financial crisis, we first examine the Turkish banking sector briefly to identify the importance of operational risk there. Then we analyze the reaction of stock returns to operational risk events. Finally we present our main conclusions and suggestions for further research.

6.2 OPERATIONAL LOSSES AND THE BANKING SECTOR IN TURKEY

The financial crisis of 2000–2001 had severe consequences on the banking sector in Turkey. The reasons for the crisis have been discussed many times in the past, but one fact has not been forgotten by bank customers and employees: the control of 15 banks was transferred to the Saving Deposits Insurance Fund (SDIF). In addition, owners of five banks were arrested (see Table 1 in Özatay and Sak 2003). It is now clear that many of the problems in the banking sector at that time were related to operational loss events, including internal and external fraud.

Despite the dreadful experience the sector went through in the late 1990s and early 2000s, operational loss capital was not required until the middle of 2007 by the Banking Regulation and Supervision Agency (BRSA). Based on the second survey results on the banking sector (BRSA 2005), about 69% of the banks planned to use the standardized approach, about 45% of the banks planned to use the basic indicator approach, about 45% planned to use the alternative standardized approach, and the rest planned to use advanced measurement approaches.[5] In addition, about 50% of the banks in the survey state that they do not classify operational losses into operational loss events.

Table 6.1 reports some banking statistics for Turkey. Except for the capital requirements for operational risk data, which is as of mid-2007, the rest of the data used in the table are as of the end of 2006. For all banks, the ratio of capital requirements for operational risk to total bank assets was 1.7%. For market risk, this ratio was 0.5%; for credit risk, it was 9.1%. As discussed in the literature (e.g., Jarrow 2008), the estimates for the necessary capital to cover operational risk are at least as large as the necessary capital to cover market risk. There is no surprise in Turkey: The estimate for operational risk, on average, is larger than the estimate for market risk.

It is no surprise that the ratio of operational risk capital to total assets is very small for development and investment banks. For deposit banks, however, the operational risk ratio increases significantly. Specifically, for state banks, this ratio is 7.3%, much larger than the ratios of domestic private banks and foreign banks. Moreover, the ratio of necessary capital for operational risk to market risk is about 18, much larger than the average of about 3 for all banks or for other depository bank classifications. This, of course, raises the question of the determination of operational risk capital amount and its effect on the firm value. Note also that total credits extended to total assets and total deposits are smaller for state banks, and their average number of branches and average number of employees are much larger.

TABLE 6.1 Descriptive Statistics for Banking Sector in Turkey

	Assets[a]	Average # of Branches	Average # of Employees	Credits/ Assets	Credits/ Deposits	Credit Risk Ratio	Market Risk Ratio	Operational Risk Ratio
All Banks	10387035	147	3070	39.9%	91.2%	9.1%	0.5%	1.7%
Deposit Banks[b]	14069822	204	4158	40.1%	91.2%	12.4%	0.7%	2.2%
State Banks	47787474	716	13074	35.6%	48.2%	25.2%	0.4%	7.3%
Domestic Private Banks	18972500	256	5230	47.8%	79.1%	18.7%	1.2%	2.9%
Foreign Banks	3954907	71	1720	36.1%	113.7%	4.7%	0.3%	0.7%
Development and Investment Banks	1180068	3	352	39.3%	—	0.9%	0.1%	0.2%

[a]1000 YTL

[b]Includes banks under the control of Savings Deposit Insurance Fund.

Except for capital requirements, 2006 year-end values are used. For capital requirements, 2007 midyear values are used.

Source: Banking Regulation and Supervision Agency; Banks Association of Turkey[6]

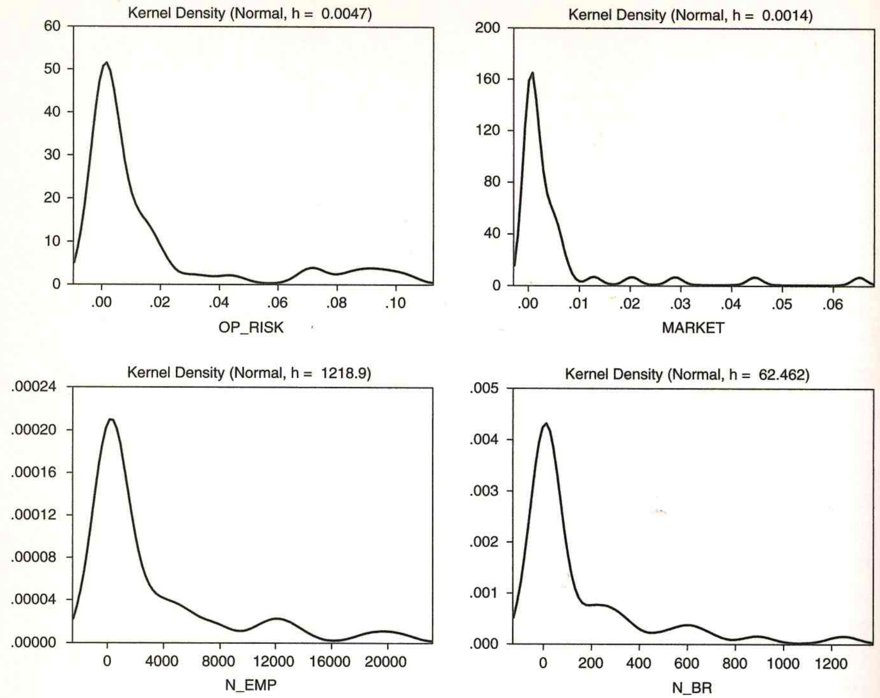

FIGURE 6.1 Empirical Distributions

Empirical distributions for operational and market risk capital, number of employees, and number of branches are presented in Figure 6.1. It is clear that all the variables selected have long right tails, indicating that few of the banks have a large number of employees, a large number of branches, and larger ratios of necessary capital for operational and market risk to total assets. It should also not be surprising that banks that are represented in the right long tail of the distribution in the four graphs are mostly the same ones.

6.3 REACTION OF STOCK RETURNS TO OPERATIONAL RISK EVENTS

The market value impact of operational loss events has not been investigated extensively in the literature. There are two reasons for this: the recent focus on the importance of operational losses and the lack of operational loss

data, except for high-severity, low-frequency events (see Cummins et al. 2006 for an event study on U.S. financial institutions). Here we conduct an event study analysis for the banking sector in Turkey. Given the availability of market price data, we focus only on a smaller segment of banks that are/were traded on the Istanbul Stock Exchange (ISE) since 1998.

We obtained the daily data of securities traded at the Istanbul Stock Exchange and the market index[7] from the web site www.analiz.com for the banks with at least one operational loss event. Since no operational loss database exists, we obtained event data by exploiting two different sources. The main source of the event data is the company news archive provided by the Istanbul Stock Exchange. This source includes mostly the legal events and events related to processes and systems. We also used newspaper archives in Turkey[8] and observed several small to large operational loss events due to mostly internal fraud. Unfortunately, in many cases, the name of the financial institution is withheld, even for the recent incidents, a fact that creates transparency issues regarding the public availability of the financial news.[9] Overall, we have identified 22 events since 1998. The events themselves indicate that banks in Turkey do not face high-severity events in general. Most of the events, in particular the fraud events, can be classified as low- to medium-severity events.

For the analysis, we employ the standard event study methodology to identify the response of stock returns to operational risk events. The abnormal returns (AR) are calculated to determine the unexpected change in the returns before or following the announcement. For the cumulative effect on returns, we use cumulative abnormal stock returns (CAR) around the specific events related to operational risk.

The following specification of the market model is used to determine the expected returns in our analysis:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{6.1}$$

where R_{it} = daily return of security i at time t
R_{mt} = market return at time t

where all returns are calculated as the log differences.

As always, we assume ε_{it} is the disturbance term satisfying the classical assumptions. We estimate the model specified with Equation 6.1 with 80 observations dating over [−100,−20] days before the event date, where a negative sign indicates the number of days before the event. Given the existence of events that fall under the legal definition of events, we keep the event window wider than usual and include 20 days before and after the event date. However, in calculating the cumulative abnormal returns, we examine three alternative event windows: event window of 7 days ($t = -3$ to $t = +3$), event window of 21 days ($t = -10$ to $t = +10$), and finally the event window of 41 days ($t = -20$ to $t = +20$). We estimate abnormal stock returns (AR_{it}) for security i at time t as the ordinary least squares (OLS) residuals defined by Equation 6.2:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) \tag{6.2}$$

The average abnormal returns for each day of the event window are reported in Table 6.2. To save space, only the event window 10 days prior and 10 days after the event is included in the table. The means of abnormal returns, as reported in the table, are oscillating around zero throughout the event window, but there does not seem to be a negative trend as we expect after an event related to operational risk. However, there does seem to be a higher dispersion at the day of the event as indicated by the standard deviation. As indicated by the kurtosis and skewness, the abnormal returns follow a leptokurtic and mostly skewed distributions across unit of observations.

TABLE 6.2 Average Abnormal Returns

Day	Average	Median	Std. Dev	Kurtosis	Skewness	Range
−10	0.083	−0.004	0.336	13.016	3.552	1.548
−9	−0.011	−0.007	0.080	2.459	−0.586	0.371
−8	0.105	−0.004	0.376	17.386	4.059	1.774
−7	−0.001	0.001	0.139	10.049	−0.397	0.891
−6	−0.050	−0.005	0.277	8.734	−2.244	1.558
−5	0.018	0.008	0.072	6.948	2.084	0.358
−4	−0.019	−0.005	0.275	11.341	−2.367	1.557
−3	−0.084	−0.005	0.472	21.048	−4.536	2.421
−2	−0.385	0.012	1.791	21.352	−4.595	8.798
−1	0.071	0.007	0.232	8.639	3.058	0.951
0	−0.239	0.006	1.296	21.365	−4.585	6.679
1	−0.085	−0.002	0.281	16.284	−3.920	1.321
2	0.002	−0.005	0.398	11.130	1.989	2.437
3	−0.089	−0.002	0.372	12.891	−3.402	1.931
4	−0.078	−0.004	0.190	3.391	−2.205	0.646
5	−0.086	−0.009	0.273	10.732	−3.320	1.162
6	0.297	0.005	1.466	21.390	4.591	7.502
7	0.033	0.005	0.084	4.359	2.101	0.353
8	−0.068	−0.012	0.320	19.786	−4.308	1.738
9	−0.032	−0.006	0.115	16.762	−3.870	0.601
10	−0.046	−0.003	0.183	16.313	−3.922	0.873

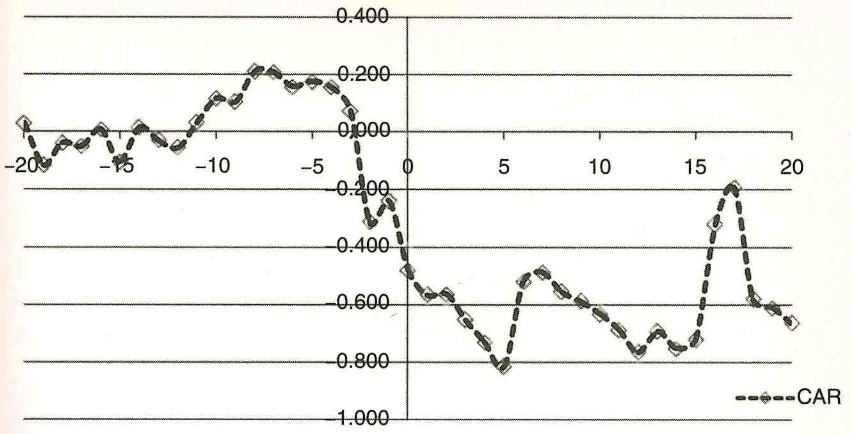

FIGURE 6.2 Cumulative Abnormal Returns (41-day event window)

The cumulative abnormal returns (CAR) for a 41-day event window—20 days before and 20 days after the event date[10]—are presented in Figure 6.2. The CAR_t for any day t inside the event window is defined as the sum of average abnormal returns (AAR_t) up to that day as $CAR(t) = \sum_{i=-t_1}^{t} AAR_i$ where t_1 represents the starting day of the event window.

As it is clear from Figure 6.2, CAR shows a declining trend starting about 4 days before the event date and continues to fall for another 5 days after the event date. Similarly, we present the calculated CAR values for 21-day and 7-day event windows in Figure 6.3. It is clear that the negative reaction of stock returns to events related to operational risk is clear with all event windows. That is, the market reacts negatively to the events related to operational risk by lowering the stock return in the short run.

It is interesting to note the market reaction to the event before the event occurs. This finding may indicate the existence of information leakage to investors before the event date. Or this finding might be caused by the late reporting of the events either by the ISE or by the newspapers. In addition, there might be other relevant information that affects investor expectations before the date of the event.

The event dates we consider for the analysis start from 1998 and end in 2007. Nevertheless, the Turkish economy, particularly the financial sector, went through a severe crisis in 2000–2001; many banks went bankrupt or were taken over by the SDIF (see Özatay and Sak 2003). Hence, it may be important to identify breakpoints and examine the behavior of CAR for subperiods. One approach is to use experience or educated guess; the

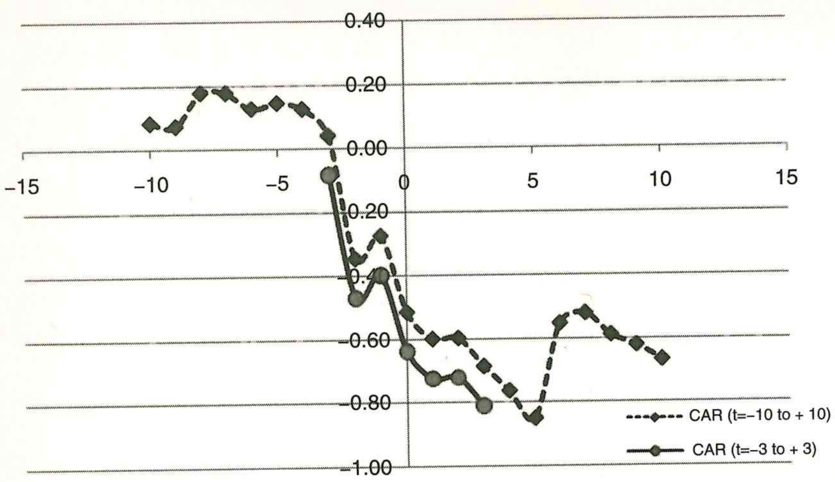

FIGURE 6.3 CAR for 21-Days and for 7-Days Event Windows

alternative is to let the data determine the breakpoints. We choose to follow the second approach and use the Iterative Cumulative Sums of Squares (ICSS) algorithm introduced by Inclan and Chao (1994). The ICSS algorithm can be used to detect multiple breakpoints in a time series by testing for volatility shifts.

To introduce the algorithm, let us assume ε_t is the series in question with zero mean and $\sigma^2{}_t$ as the unconditional variance. Inclan and Chao (1994) define cumulative sum of squares between time 1 and k as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \qquad \text{where } t = 1, \ldots, T \quad \text{and} \quad k = 1, \ldots, T$$

The centered and normalized cumulative sum of squares until time k is represented by the D_k statistics.

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad \text{with } D_0 = D_T = 0$$

If there is no volatility shift in the series, the plot of D_k against k will oscillate around zero. With a volatility shift, however, we will observe D_k statistics drifting away from zero. Based on Inclan and Chao's (1994) study, an asymptotic critical value of 1.358 can be used to create boundaries to identify the point in time with a volatility shift.[11]

We used monthly returns for the market portfolio, namely ISE100, to identify the sudden changes in volatility. The source of data was the ISE.[12] The breaks predicted by the ICSS algorithm are consistent with our expectation.[13] The ICSS algorithm identified one breakpoint. Thus, the first period, January 1995 to October 2001, corresponds to the pre-2001 financial crisis in Turkey, and the second subperiod, post-October 2001, corresponds to the stable and growth environment with the banking sector closely monitored by BRSA and regulations updated in accordance with the standards. Although not reported here, the first subperiod corresponds to a higher return and standard error than the second subperiod, indicating a higher-risk, higher-return environment.

Based on the outcome of volatility shifts, we recalculated CARs for pre- and post-2002 events. Out of 22 events, 12 belong to the first subperiod and the rest to the second subperiod. The CARs for 21-days event window for both subperiods are displayed in Figure 6.4.[14] Given the high-risk environment with loose regulations in the banking sector, we expect stock return reaction to operational risk events to be more significant and negative in the first subperiod.

As expected, we observe a declining trend in CAR_t values for the pre-2002 period several days before the announcements. However, the values of CAR_t at time t for the post-2001 period appear to be quite small, and there does not seem to be a trend in either the positive or the negative direction. We believe we can argue that the reaction of stock returns to operational risk events is weaker, though not with strong evidence, for the post-2001

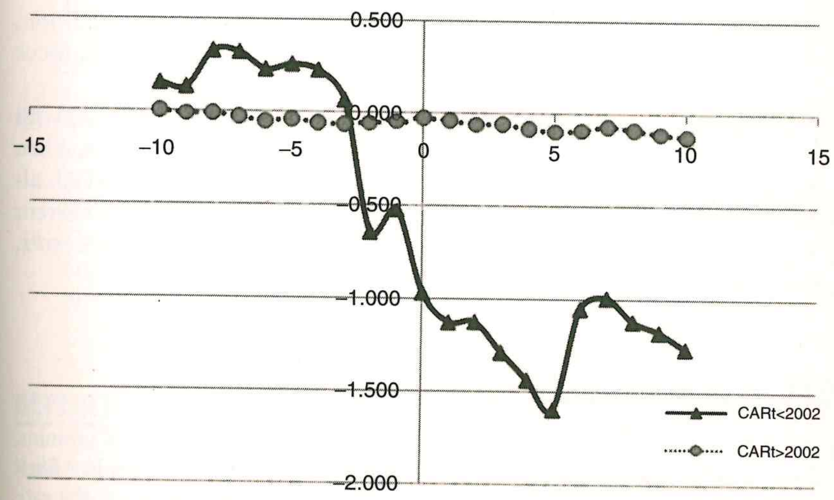

FIGURE 6.4 CARs and Pre-2002 and Post-2001 Events

period mostly due to effective regulation of the banking sector. In addition, other high-severity events that were not included in the data could cause a multiplier effect on the market response before the 2001 period.[15]

6.4 CONCLUSION

The importance of operational risk for the financial sector has increased dramatically following several costly and public events, with the latest high-severity event being the unauthorized trading loss at the Société Générale bank. The banking sector in Turkey experienced a severe crisis in the early 2000s. The crisis was due in part to economic conditions at that time and in part due to events that fall under the definition of operational risk. As a result of the problems, ownership for many banks was transferred to SDIF. The estimation of capital requirements for operational risk, however, did not start until the middle of 2007, with most banks using the standardized or basic indicator approach for the estimation. Consistent with the findings in this specific literature, the capital requirements are higher for operational risk than the market risk.

We also investigated the reaction of stock returns to operational risk events through a classical event study analysis. Since there was no database of operational risk events, we scanned through news archive for the banks that are/were trading at the Istanbul Stock Exchange. We also analyzed the archives of major newspapers with respect to fraud-related events. Overall, we identified 22 events. We believe the low number of events was caused by two factors: not all events are revealed to the public and, if the event is revealed to the public, the institution name is kept confidential. In addition, many of the events in Turkey are low-severity events that limit public focus on that area, particularly after 2002.

We find negative stock return reaction to operational risk events, with the reaction starting several days earlier than the event date. However, when we take into account the structural breaks, identified through the ICSS algorithm, we observe that the reaction loses its significance for the current period. That is, for the pre-2002 period, returns react negatively to events, but this finding does not hold for the post-2001 period.

NOTES

1. Some other examples are: Allied Irish Bank's loss of $740 million (Cummins, Lewis, and Wei 2006), the loss of $691 million due to rogue trading in Allfirst Financial, the Household Finance settlement charge of $484 million, the estimated loss of $140 million because of the September 11 attack on the Bank

of New York (Fontnouvelle et al. 2003). The blackout in New York City on August 14, 2003, is also an example of operational risk for institutions there due to "business disruption and system failures." Similarly, the August 1999 major earthquake in Turkey can fall under the same event definition.
2. Fontnouvelle et al. (2003) indicate that there were more than 100 events with operational losses exceeding $100 million in the last decade. In addition, many operational losses were not publicly announced, and many low-severity, high-frequency events do not get public attention.
3. For a clear discussion on other gains and problems, see Wahlström (2006).
4. For Japan, the leading events are "external fraud" and "execution, delivery and process management" events in terms of the number of losses. In addition, the concentration of losses is under the retail banking business line (Bank of Japan 2007).
5. For details on the measurement approaches, see BCBS (2006).
6. Both organizations provide bank-level data through their web pages: www.bddk.org.tr and www.tbb.org.tr, respectively.
7. The market index is called ISE100 and includes 100 firms traded on the Istanbul Stock Exchange.
8. The newspapers we used are *Hürriyet, Milliyet,* and *Sabah*. In terms of market share, these three papers have the lion's share. They can be accessed freely through these web addresses: www.hurriyet.com.tr, www.milliyet.com.tr, and www.sabah.com.tr.
9. An example is the internal fraud loss of about $13 million from a bank branch in Turkey in March 2008. Although the loss was publicly announced, the name of the financial institution name was not.
10. Note: We use the public announcement date as the event date.
11. Critical values are calculated from the distribution of D_k under the null hypothesis of homogeneous variance. One can use the critical values to obtain upper and lower boundaries to detect volatility shifts. For details on the ICSS algorithm and some uses, please see: Inclan and Chao (1994), Ewing and Malik (2005), Marcelo et al. (2008).
12. www.imkb.gov.tr.
13. We could say our experience or educated guess would be correct, and it could save a lot of time in this special case.
14. Since the 21-day window was sufficient to produce required information in earlier figures, we present CARs only for that specific event window.
15. The bankruptcies in the banking sector and the transfer of control to SDIF led investors and customers to view banks as having lower credibility around that time, and any information available became important.

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PART Two

Operational Risk Measurement: Quantitative Approaches