Total Risk Composition of BIST100 Index Manufacturing Companies

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Abstract

In this study, we examined the total risk composition of the manufacturing firms in the BIST100 Index during the period of October 1998 – June 2013. Although the total risk composition is generally stated as the sum of systematic and unsystematic risks, in this study, this structure has been analysed under internal (asset-liability) and external (market) risk factors. In order to define the total risk composition of the selected firms, we performed panel data analysis via Pooled OLS, Fixed Effect and Random Effect models in the first part of empirical section. Due to the fact that there have been assumitional problems in the Random Effect Panel Data Model, in the second part, we carried out the Fitting Generalized Least Square (FGLS) panel data analysis. According to our findings, external risk factors have relatively lower effects within the total risk composition of companies examined. These results are not consistent with the findings of studies concerning emerging markets.

Key Words Total Risk, Internal Risk, External Risk, Panel data, Volatility.
JEL Classification Codes C33, G10, G30, G32
1. Introduction

Basic concepts of the finance theory consist of risk and return. When the literature is analysed, it is seen that almost all seminal studies have used these parameters in financial modelling. Although defining and measuring of return is relatively easier, it is not possible to do the same for measuring risk. Due to this reason, there have been different methods in finance literature on modelling risk, from standard deviation, to ARCH-GARCH type, and stochastic models. As stocks are risky securities, properly defining and measuring risk is a vital issue in the analysing of these securities.

So far, the risk structure of firms has been researched in many academic studies comprehensively. While some of them have been done on systematic risk, others analysed total risk of firms. In these studies, it has been seen that their independent variables generally consist of return variables (see Fama and French (1992), Serra (2002), Ammann and Steiner (2008)). However, in this study we oppose this approximation using the risk-risk model. While the existence of the risk and return relationship has been accepted, we believe the model that only consists of risk parameters will be more convenient in the modelling of risk for any asset, firm or country. In the case that total risk of a firm is stated as a standard deviation of stock returns, then the standard deviation will be a simple measure of the volatility of this stock, as well. The total risk of the firm and other relationships can be written down in the following way

\[ \sigma_t^2 = \beta_t^2 \sigma_m^2 + \sigma_{te}^2 \]  

Total Risk = Systematic Risk + Unsystematic Risk  

Total Risk = Market Risk + Firm Speisific Risk  

Firm Speisific Risk = Assets Risk + Liabilities Risk

In this study, it is accepted that when the total risk of a firm is stated as the standard deviation of its stock returns as above, factors which are effective on sigma can be summed up as internal and external risk parameters. It can be expressed that if internal risks are the specific risk of firm, then external factors will be the market risk that the firm belongs to.

From this point forth, we put forward a hypothesis in this study. It states that total risk composition of any firm can consist of internal and external risk factors. If we are talking about internal risk factors, they should come from the balance sheet or income statement. That is why we presented two measures as internal risk factors of any firm. The first one is the cash to short term debt ratio measurement of the asset risk of a company. The second one is the short term debt to total liabilities ratio that measures the liabilities risk of any firm as an indicator of liquidity crunch. On the other hand, we have used market price volatility as a
market risk variable. Of course, we can produce different kinds of measurements as a risk proxy for any firm. For instance; financial risk measurements, business risk measurements, etc. However, we wanted to see the effect of the size of the market risk, and we limited internal risk factors. Because there is a general acceptance in finance literature, emerging markets have high volatility in comparison to developed markets. Is there a significant share of this risk within the companies’ total risk? In the empirical part we will criticize the argument about the previous question stated.

2. Related Literature

Although there is wide literature for risk-return relationship and systematic risk determinants of the firms, we have not seen any model that uses only risk parameters in denoting the firm’s systematic or total risk. Related arguments on this issue have been presented below:

Sharpe (1964), the developer of the Capital Asset Pricing Model, decomposed the total risk of a portfolio into systematic and nonsystematic risks. After the seminal paper of Sharpe (1964), determinants of systematic and nonsystematic risks have been widely discussed in finance literature. One of the early studies was conducted by King (1966); he stated that the market-wide effects could be significant over the variability of stock returns in the range of 30% to 40%. Ball and Brown (1968) focused on the accounting income and stock prices. They concluded that there was a strong relationship between income surprise and abnormal stock price returns. Mandelker and Rhee (1984) analysed the impact of operating leverage and financial leverage to capital structure on systematic risk. Empirical findings showed that the degrees of operating and financial leverage could explain the large part of the variation in beta. They also stated that there was a significant correlation between operating leverage and financial leverage.

After the 1990’s, the number of risk/return studies on stocks increased progressively. Fama and French (1993) defined 3 important risk factors related to stock returns: they are an overall market factor, factor related to firm size and book-to-market equity. Similarly, Chou et al. (2004) examined the explanatory power of size and book-to-market in the cross-section of stock returns over various sample periods. On the other hand, Lettau and Ludvigson (2001) stated that volatility in the total consumption–wealth ratio is good predictor of both real stock returns and excess returns over a Treasury bill rate. Hawawini and Keim (1997) reviewed the evidence on the cross-sectional behavior of common stock returns in the U.S. and other equity markets. They stated that despite the premium of return being significant in most international stock markets, it is uncorrelated across markets. Demsetz and Strahan (1997) showed that better diversification does not provide lower risk. Because, according to their findings, risk-
reducing potential of diversification at large bank holding companies was offset by their lower capital ratios and larger commercial and industrial loan portfolios. Unlike the majority of the literature, Gu and Kim (1998) examined the systematic and unsystematic risks of casino stocks, and the determinants of their systematic risk. They demonstrated that 92 percent of the examined casino stocks’ was contributed by firm-specific unsystematic risk. Bradley et al. (1998) explored the effect of expected cash-flow volatility as a determinant of dividend policy. Their results showed that managers rationally pay out lower levels of dividends when future cash flows are less certain given the existence of a stock-price penalty associated with dividend cuts.

In addition to the above studies, there is a great deal of interest to dividend policy and stock price volatility relationships in finance literature. As shown in one of the early studies, Allen and Rachim (1996) performed a cross-sectional regression in order to explain the linkage between stock price volatility and the dividend policy of the firm. Ackert and Smith (1993) analysed the effect of share repurchases and takeover distributions, in addition to cash dividends. The impact of the dividend policy over the stock price has been documented in different papers more recently, such as Rashid and Rahman (2008), Profilet and Bacon (2013) and Habib et al. (2012). Ludvigson and Ng (2007) found new evidence for volatility and excess returns. They stated that volatility, risk premium, and real factors present important information about one-quarter-ahead excess returns and volatility not contained in commonly used predictor variables.

Similar to the study of King (1966), Aquino (2002) showed that systematic risk can be managed at the macro level by regulating macroeconomic fluctuations. Also, the findings of Al-Qaisi (2011) support these results. He stated that several factors including size, financial leverage, government deficit and inflation rates significantly affect a company’s systematic risk value in the Amman Stock Exchange. More recent studies of the risk structure of the stock market have analysed the systematic risk structure of stock returns. For instance, Hooy and Lee (2010) analysed the determinants of systematic risk exposures of the airline industry in Japan, Korea, Hong Kong, Taiwan, Singapore, Malaysia and Thailand between 1996 and 2009 via the panel data method. They showed that only size and operating efficiency are positive and significantly related to systematic risk, while airline safety is significant and negatively associated with the systematic risk. Kachecha and Strydom (2011) proposed the use of accounting-based measures of systematic risk as an alternative to the market beta for the Johannesburg Stock Exchange (JSE) and found that there is a statistically significant relationship between the measures of earnings variability, size, and systematic risk. Amorim et al. (2011) presented empirical evidence on the relationship between accounting information and systematic risk in the Brazilian market with the panel data analysis. According to the
findings, some accounting betas may explain the market beta through a forecasted manner, these accounting betas enhance the prediction of the market beta when compared with historical market betas.

More recently, Tanrıöven and Aksoy (2011) analysed the determinants of systematic risk on a sectorial basis in BIST trading companies between 1997-2009 using the non-balanced regression method. They showed that beta has a positive relationship between debt ratios, and sales growth has an effect on beta in all sectors, except for food and technology. Biase and Apolito (2012) provided an insight to the main determinants behind the systematic risk of Italian banks listed on the Milan Stock Exchange from 1992 to 2011. The results have indicated that the bank equity beta correlates positively with the bank size and with the relative volume of loans and intangible assets, and negatively with bank profitability, liquidity levels and loan loss provisions. Iqbal and Shah (2012) explored the relationship among financial variables and systematic risk. Their results showed that liquidity, profitability, operating efficiency, firm size, dividend payout and market value of equity are statistically significant to explain systematic risk. Zhang et al. (2013) adopted volatility of stock return as the measure for total risk, and beta as the measure of systematic risk; risk-adjusted-returns are measured by the Sharpe ratio and the Treynor ratio. They found that US insurers’ risk and reward-to-total risk are significantly related to firm-specific factors.

This paper will extend the definition of the risk approach using only the risk parameters in the modelling. The remainder of the paper is structured as follows: In section three we will give theoretical information on the panel data modelling, section four will provide empirical results, and in the last section we will present the conclusion of the overall study.

3. Model Specification

In this study, alternative panel data methods have been used in order to capture the nature of cross section and the time dimension of the data. A panel data includes properties of both time series and cross-section data (Gujarati, 2004). By providing sequential observations for a number of individuals, panel data allows us to build a model to account for both heterogeneity across individuals and for dynamic effects. Thus, it can be used to test more complicated models than the ones included in a single time series, or cross section data (Hsiao, 2003). Because of increasing availability of panel data, panel data regression models are being used more frequently by researchers in many fields (Gujarati, 2004). Alternative panel data models are explained in the following sections.

3.1 Pooled OLS

The Pooled OLS method estimates one joint constant for all cross-sections using common \( \alpha \) and the slope vector \( \beta \) without dummy variables. If heterogeneity or individual effect
(cross-sectional or time specific effect) does not exist, the Pooled OLS provides efficient and consistent estimates (Greene, 2010). The Pooled OLS model is shown below:

\[ y_{it} = \alpha + \beta x_{it}' + \epsilon_{it} \]  

(5)

where \( \epsilon_{it} \) presents the differences between cross-sections, or cross-sections and time variable (Park, 2011).

### 3.2 Fixed Effect Model

Unlike the Pooled OLS method, in the fixed effect model, the intercept is allowed to vary from individual to individual, the fact that the slope parameters are assumed to be constant in both dimensions (Mátyás and Sevestre, 2008). The generalization of the Pooled OLS for panel data is to introduce dummy variables, which absorb the panel variations that are consistent across time, to allow for the effects of those omitted variables that differ among panels but are constant over time, and the effects that are specific to each time period but are the same for all panels (Hsiao, 2003).

Given a panel model where the intercept and all slope parameters are constant for the sample of \( N \) individuals over \( T \) periods, can be presented as following way:

\[ y_{it} = \alpha_0 + \beta_1 x_{1it} + \cdots + \beta_K x_{Kit} + \epsilon_{it}, \quad i = 1, \ldots, N; \ t = 1, \ldots, T \]  

(6)

\[ y_{it} = \alpha + \beta x_{it} + \epsilon_{it} \]  

(7)

where \( y_{it} \) is the dependent variable (for individual \( i \) at time \( t \)), \( x_{it}' \) is the \( K \) row vector of the independent variables, \( \epsilon_{it} \) is a non-observable random term, \( \beta \) is the \( K \) column vector of the slope parameters and \( \alpha_0 \) is the intercept (Mátyás and Sevestre, 2008). If we want to consider “individuality” for each cross-sectional unit, we should let the intercept differ for each panel, while the slope coefficients are constant across panels (Gujarati, 2004). As stated by Mátyás and Sevestre (2008) when different intercepts are permitted for the \( N \) individuals, the fixed effect model becomes as follows:

\[ y_{it} = \alpha_i + \beta x_{it} + \epsilon_{it} \]  

(8)

Schmidheiny (2013) showed that the \( T \) observations for individual \( i \) can be summarized as:

\[ y_i = \begin{bmatrix} y_{i1} \\ \vdots \\ y_{iT} \end{bmatrix}, \quad x_i = \begin{bmatrix} x_{i1}' \\ \vdots \\ x_{iT}' \end{bmatrix}, \quad \epsilon_i = \begin{bmatrix} \epsilon_{i1} \\ \vdots \\ \epsilon_{iT} \end{bmatrix} \]  

(9)

and \( NT \) observations for all individuals and time periods as:

\[ y_i = \begin{bmatrix} y_{11} \\ \vdots \\ y_{n1} \\ y_{1T} \\ \vdots \\ y_{nT} \end{bmatrix}, \quad x_i = \begin{bmatrix} x_{11}' \\ \vdots \\ x_{n1}' \end{bmatrix}, \quad \epsilon_i = \begin{bmatrix} \epsilon_{11} \\ \vdots \\ \epsilon_{nT} \end{bmatrix} \]
The term “fixed effects” means that although the intercept may vary for all individuals, each individual’s intercept does not differ over time (Gujarati, 2014).

### 3.3 Random Effects Model

Just as for the fixed effects model, which allows only the unobserved individual effects, with the random effects model we can also allow for time variation. In the case of time variation, a time period-specific error term is included to the model. The random effects panel model can be presented as follows (Brooks, 2008):

\[
y_{it} = \alpha + \beta x_{it} + \omega_{it}, \quad \omega_{it} = \epsilon_{i} + u_{it}, \quad u_{it} \sim IID(0, \sigma_{it}^2); \quad \epsilon_{i} \sim IID(0, \sigma_{\epsilon}^2)
\]  
(11)

where \(\omega_{it}\) functions as an error term. The error term is not correlated with the predictors, therefore time-invariant variables turn into explanatory variables. \(\omega_{it}\) can be decomposed into two components: an individual specific component, which does not vary over time, and a remainder component, which is assumed to be uncorrelated over time (Verbeek, 2008). In the random effects model there are no dummy variables in order to take the heterogeneity (variation) in the cross-sectional dimension into account. Instead, the variation is considered via the \(\epsilon_{i}\) terms (Brooks, 2008).

### 4. Data Description and Modelling

This section seeks to develop a model in order to estimate total risk composition of selected Turkish stocks listed in the BIST100 Index. Although there is a collection of literature that identifies the determinants of stock returns, studies for the risk determinants of stocks are relatively low. On the other hand, existing literature on this matter analyses the risk-return relationship with return as a dependent variable and risk as an independent variable. Contrary to this approach, we analysed the risk-risk model with a dependent variable, which is a risk parameter, and independent variables, which are also risk parameters, via panel data methodology. The aim of modelling this is to see which variables explain the total risk composition of manufacturing firms in the BIST100 Index. In accordance with this purpose, we have used different data related to the BIST100 Index manufacturing firms that have close beta values in order to prevent bias in the results. Along with the study, we used the model below concerning the dependent variable as follows:

\[\sigma_{\text{return,3m}} = \alpha + \beta_1 IR_{\text{asset}} + \beta_1 IR_{\text{liability}} + \beta_3 ER_{\text{BISTvol}} + \beta_4 \epsilon_{it}\]  
(12)
where dependent variable ($\sigma_{\text{return,3m}}$) is the 3 month standard deviations of selected companies from the BIST100 Index. These standard deviations were calculated from the daily frequency returns of the related stocks using the equation: 
\[ \sqrt{\frac{\sum_{i=1}^{n}(r_i-\mu)^2}{n-1}}. \]
As the balance sheet data has a 3 month frequency, we have calculated 3 months of standard deviations of the daily returns in order to provide harmonisation among the dependent and independent variables.

Regarding independent variables, they consist of internal and external risk factors. We split the internal risk factors into two ratios, the first one is the asset risk ratio ($1R_{\text{asset}}$), and the second one is the liabilities risk ratio ($\text{short term debt to total liabilities ratio} - 1R_{\text{liabilities}}$). As an external risk parameter, we used the BIST100 Index 3 months volatility ($ER_{\text{BISTvol,3m}}$), derived from the daily returns of the BIST 100 Index. When it is compared to developed stock exchanges, it is clear that the BIST100 Index, and included stocks, have a very high volatility structure (see Estrada (2000) and Harvey (1995)). Subsequently, it is expected that $ER_{\text{BISTvol,3m}}$ will be an important variable in the model according to existing literature. Data used in this study can be seen in Table 1 with the respective codes:

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Meaning</th>
<th>Time interval</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>c_total_risk</td>
<td>Company total risk</td>
<td>October 1998 – June 2013</td>
<td>quarterly</td>
</tr>
<tr>
<td>ctostd</td>
<td>Cash to short term debt</td>
<td>October 1998 – June 2013</td>
<td>quarterly</td>
</tr>
<tr>
<td>stdtol</td>
<td>Short term debt to total liabilities</td>
<td>October 1998 – June 2013</td>
<td>quarterly</td>
</tr>
<tr>
<td>bist_p_v</td>
<td>BIST100 price volatility</td>
<td>October 1998 – June 2013</td>
<td>quarterly</td>
</tr>
</tbody>
</table>

While the beta is used as a systematic risk measure in finance literature, Estrada (2000) stated that since high volatility of these markets, and the emerging market’s integration problem to the developed markets, robustness of beta becomes lower, therefore we left the beta out of the model. In spite of that, in order to raise credibility of the test results, we selected the companies that have similar beta values. The purpose of this study is to see the effect of risk factors that consist of total risk, except for beta. Hence, we determined the manufacturing firms that traded under the BIST100 Index, then 31 firms with relatively close beta values, were incorporated into the model.
Table 2. Beta Values of the Companies

<table>
<thead>
<tr>
<th>No</th>
<th>Company</th>
<th>β</th>
<th>No</th>
<th>Company</th>
<th>β</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>afyoncim</td>
<td>0.529273</td>
<td>17</td>
<td>izmirdcelik</td>
<td>0.867921</td>
</tr>
<tr>
<td>2</td>
<td>akcansa</td>
<td>0.853218</td>
<td>18</td>
<td>kartonsan</td>
<td>0.461059</td>
</tr>
<tr>
<td>3</td>
<td>aksa</td>
<td>0.789014</td>
<td>19</td>
<td>konyacim</td>
<td>0.612098</td>
</tr>
<tr>
<td>4</td>
<td>anadolucam</td>
<td>0.818275</td>
<td>20</td>
<td>kardemir</td>
<td>0.987396</td>
</tr>
<tr>
<td>5</td>
<td>arcelik</td>
<td>0.965081</td>
<td>21</td>
<td>mutluaku</td>
<td>0.737977</td>
</tr>
<tr>
<td>6</td>
<td>anadoluisuzu</td>
<td>0.887833</td>
<td>22</td>
<td>otokar</td>
<td>0.830007</td>
</tr>
<tr>
<td>7</td>
<td>ayzgaz</td>
<td>0.815216</td>
<td>23</td>
<td>petkim</td>
<td>0.909195</td>
</tr>
<tr>
<td>8</td>
<td>bagfas</td>
<td>0.867575</td>
<td>24</td>
<td>omvpetroil</td>
<td>0.822670</td>
</tr>
<tr>
<td>9</td>
<td>brisa</td>
<td>0.724951</td>
<td>25</td>
<td>sasa</td>
<td>0.766353</td>
</tr>
<tr>
<td>10</td>
<td>borusan</td>
<td>0.738824</td>
<td>26</td>
<td>tofas</td>
<td>0.992532</td>
</tr>
<tr>
<td>11</td>
<td>eregli</td>
<td>0.966296</td>
<td>27</td>
<td>turcas</td>
<td>0.895439</td>
</tr>
<tr>
<td>12</td>
<td>fordotosan</td>
<td>0.886082</td>
<td>28</td>
<td>trakycam</td>
<td>0.846707</td>
</tr>
<tr>
<td>13</td>
<td>goltascim</td>
<td>0.713296</td>
<td>29</td>
<td>tpras</td>
<td>0.219551</td>
</tr>
<tr>
<td>14</td>
<td>goodyear</td>
<td>0.682695</td>
<td>30</td>
<td>ulker</td>
<td>0.792843</td>
</tr>
<tr>
<td>15</td>
<td>gubrefab</td>
<td>0.853332</td>
<td>31</td>
<td>vestel</td>
<td>0.948497</td>
</tr>
<tr>
<td>16</td>
<td>hurriyetg</td>
<td>1.044151</td>
<td>32</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

As it can be seen from Table 2, there are no serious deviations in the beta values of the selected companies. The obtained beta values, except for three, are between 0.50 and 1.00; the companies that are out of this range are hurriyetg, tpras and kartonsan. Due to the same reason that these companies are out the range, we submitted the below graph, which represents the heterogeneity across countries results, as an another similarity measure. As it is seen, while there are no serious deviations from the mean, companies that have a significant effect on the mean can be listed as afyoncim, arcelik, bagfas, borusan, fordotosan, goltascim, goodyear, konyacim, kardemir, petkim, trakycam.

Figure 1. The heterogeneity across countries

![Figure 1. The heterogeneity across countries](Image)
While it is explained by Baltagi (2005) that the panel data methodology can lower the multicollinearity problem, we present the correlation matrix between independent variables in Figure 2. According to the results, the correlation values between independent variables are extremely low. On the other hand, it is seen that while there is a negative correlation between bist_p_v and ctostd, the correlation of stdtotl and ctostd is positive. However, all correlation values are under |0.05|.

As nonstationary variables can produce spurious results, stationarity has a great importance in financial time series analysis. Therefore, before we conduct the empirical tests, we have implemented unit root tests via LLC (Levin, Lin, Chu – Common Root) and IPS (Im, Pesaran, Shin – Individual Root). Results showed that all time series are stationary, I(0).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Common Root – (Levin, Lin, Chu) Test level</th>
<th>Individual Root – (Im, Pesaran, Shin) Test level</th>
</tr>
</thead>
<tbody>
<tr>
<td>bist_p_v</td>
<td>-24.9670 (0.0000) I(0)</td>
<td>-34.0133 (0.0000) I(0)</td>
</tr>
<tr>
<td>c_total_risk</td>
<td>-14.0205 (0.0000) I(0)</td>
<td>-12.2987 (0.0000) I(0)</td>
</tr>
<tr>
<td>ctostd</td>
<td>-9.66601 (0.0000) I(0)</td>
<td>-9.49960 (0.0000) I(0)</td>
</tr>
<tr>
<td>stdtotl</td>
<td>-5.36671 (0.0000) I(0)</td>
<td>-3.98229 (0.0000) I(0)</td>
</tr>
</tbody>
</table>

5. Empirical Results
After we acquired the results of the unit root tests, we conducted three different estimates via Pooled OLS, Fixed Effect, and Random Effect Panel Data Models. Results indicated that, contrary to our expectations, ctostd and stdtotl variables are not significant for all confidence intervals. Another unexpected result is they have a quite low value despite the significance at the 95 percent confidence interval. Despite the fact that high volatility is a general acceptance

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for the emerging markets (see Bekaert and Harvey (1997), Santis and İmrohoroğlu (1997), Aggarval et al.(1999)), it can be seen from the results below that the portion of the market volatility within the total risk of the BIST100 Index manufacturing firms is quite low.

### Table 4. Panel Data Models’ Results

<table>
<thead>
<tr>
<th></th>
<th>Pooled OLS</th>
<th>Fixed Effect</th>
<th>Random Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t</td>
<td>Coefficient</td>
</tr>
<tr>
<td>ctostd</td>
<td>-0.0002</td>
<td>-0.11</td>
<td>-0.0036</td>
</tr>
<tr>
<td></td>
<td>(0.0021)</td>
<td></td>
<td>(0.0019)</td>
</tr>
<tr>
<td>stdtotl</td>
<td>0.5310</td>
<td>1.64</td>
<td>0.5481</td>
</tr>
<tr>
<td></td>
<td>(0.3230)</td>
<td></td>
<td>(0.2916)</td>
</tr>
<tr>
<td>bist_p_v</td>
<td>0.0004**</td>
<td>6.75</td>
<td>0.0004**</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td></td>
<td>(0.0001)</td>
</tr>
<tr>
<td>const</td>
<td>-0.0188</td>
<td>-0.12</td>
<td>-0.0092</td>
</tr>
<tr>
<td></td>
<td>(0.1519)</td>
<td></td>
<td>(0.1361)</td>
</tr>
<tr>
<td>F Test</td>
<td>16.46**</td>
<td></td>
<td>21.61**</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0264</td>
<td></td>
<td>0.0250</td>
</tr>
</tbody>
</table>

Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively.

In order to determine the most accurate model between Pooled OLS, Fixed Effect and Random Effect Models, we used the Breusch-Pagan LM and Hausman tests. Table 5 shows that the $x^2$ statistic values of the LM test reject the null hypothesis, meaning that the random effect model is more convenient in comparison to the Pooled OLS estimation. On the other hand, we used the Hausman test to determine whether to use the random effect or fixed effect model. These test results showed that the null hypothesis is accepted under the 95 percent confidence interval, meaning that the random effect model is more reliable than the fixed effect model.

### Table 5. Model Selection Test Results

<table>
<thead>
<tr>
<th>Model Selection Test</th>
<th>Test Type</th>
<th>Test Statistic</th>
<th>Probability Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breusch-Pagan Lagrange Multiplier Test</td>
<td>$x^2$</td>
<td>2009.98</td>
<td>0.0000</td>
</tr>
<tr>
<td>Hausman Test</td>
<td>$x^2$</td>
<td>7.3</td>
<td>0.0629</td>
</tr>
</tbody>
</table>

Although we have choosen the accurate model to use, in the case of unsatisfying assumptions, the model will be unreliable. That is why we performed Pesaran’s (2004) cross sectional independence test on the residuals of the random effect model to see whether the residuals are correlated across entities. According to the test results ($x^2 = 61.307$), there is a dependence in the residuals of the random effect model. Also, in order to set forth whether there is a heteroskedasticity in the residual structure of panels or not, we used the likelihood-ratio test, defined by Wiggins and Poi (2001). The null hypothesis of the test states that there is no autocorrelation in the cross-sectional residuals. But, as the resultant chi-square value
was bigger than the reference figure, we rejected the null hypothesis because it means that there is autocorrelation in the residuals of the model.

Table 6. Autocorrelation and Heteroskedasticity Test Results

<table>
<thead>
<tr>
<th>Assumption Tests</th>
<th>Test Type</th>
<th>Test Statistic</th>
<th>Probability Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pesaran Cross Sectional Independence Test</td>
<td>$\chi^2$</td>
<td>61.307</td>
<td>0.0000</td>
</tr>
<tr>
<td>Poi and Wiggins LR Test</td>
<td>$\chi^2$</td>
<td>8599.00</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

In the next step of the analysis, we used a more flexible model, the fitting generalized least squares (FGLS) in order to consider these two problems. This model can generalize the basic assumptions regarding the variance-covariance matrix, residual distribution, and it is able to overcome these violations of heteroskedasticity and cross-sectional correlation assumptions (Miseman et al, 2013). FGLS allows estimation in the presence of AR(1) autocorrelation within panels, and cross-sectional correlation and heteroskedasticity across panels.

We presented both of the results, the first one allows for only heteroskedasticity, and the second one allows for both heteroskedasticity and cross sectional correlation. Results showed that in the case of allowing heteroskedasticity and cross sectional correlation in the FGLS model, stdtotl and ctostd variables would be significant at all confidence levels, as distinct from previous results.

Table 7. Fitting Generalized Least Square Results

<table>
<thead>
<tr>
<th>Cross-sectional time-series FGLS regression (Panels: Heteroskedastic)</th>
<th>Cross-sectional time-series FGLS regression (Panels: Heteroskedastic with cross-sectional correlation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient (z)</td>
<td>Coefficient (z)</td>
</tr>
<tr>
<td>---------------------------</td>
<td>----------------------------------------------</td>
</tr>
<tr>
<td>ctostd 0.0056 (0.0068)</td>
<td>0.0093** (0.0016) 5.47</td>
</tr>
<tr>
<td>stdtotl -0.0901 (0.0958)</td>
<td>0.1808** (0.0153) 11.79</td>
</tr>
<tr>
<td>bist_p_v .0002** (0.0001)</td>
<td>0.0004** (0.0001) 18.59</td>
</tr>
<tr>
<td>const 0.0001 (0.0404)</td>
<td>0.0962** (0.0482) 1.99</td>
</tr>
</tbody>
</table>

Wald chi² (3) 100.70 543.91
Estimated cov. 31 496

Standard errors are within the parenthesis. * and ** indicates the 95% and 99% confidence level, respectively.

All independent variables are statistically significant in the last panel data model for the 95 percent confidence interval. On the other hand, the effect rank of the variables, which consist of the total risk composition of manufacturing firms of the BIST100 Index, have changed. New rank is stdtotl, ctostd, and bist_p_v (0.1808372, 0.0093011 ve 0.0004085)
respectively. That being said, when we consider the risk factors, it is clear that the most effective variable on the total risk composition of our model is stdtotl, and the last one is the BIST100 Index price volatility as an external risk component.

6. Conclusion

In this study, the risk composition of manufacturing firms in the BIST100 Index was defined by internal and external risk components. In the context of asset and liability risk, internal variables were consisted of the short term debt to total liabilities ratio and the cash to short term debt ratio. On the other hand, volatility of the BIST100 Index was used as a external risk measure. According to the results under the FGLS panel data analysis, internal risk components have more weight than the external component within the total risk composition of manufacturing companies. While there is a general acceptance related to the high level of volatility of emerging markets, we have seen that the market risk of Turkey has a relatively lower effect within the total risk composition of manufacturing companies.
References


Indiana University, rt.uits.iu.edu/visualization/analytics/docs/panel-docs/panel3.php


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Appendix 1. 3 Monthly Volatilities of the BIST100 Index Manufacturing Firms

[Diagram of 3 monthly volatilities of the BIST100 Index Manufacturing Firms showing different companies and their volatilities over time.]