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What determines the differences in idiosyncratic volatility between Swedish firms and comparable European firms?

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Abstract

Firms’ stock return volatility varies across countries, and the factors driving the volatility can contribute both positively and negatively to economic growth. We show that across 3,673 firms during the time interval 2001 to 2016, stocks of Swedish firms have on average lower volatility compared to stocks of foreign European firms of similar size, age, and market-to-book value. The lower volatility for Swedish firms is more distinct and persistent in idiosyncratic volatility compared to systematic volatility. Further, our results indicate that the difference in idiosyncratic volatility is explained by Sweden having greater equity market development and less country risk compared to other European countries.

Keywords: Total volatility, systematic volatility, idiosyncratic volatility, Fama-French three-factor model, propensity score matching, panel regression

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1 Introduction

Firms' stock return volatility varies across countries (Irvine & Pontiff, 2009). Although stock return volatility is a measure of risk, which investors typically require compensation to bear (Bodie, Kane, & Marcus, 2014, ss. 127-135), the economic drivers of stock return volatility can contribute both positively and negatively to economic growth. Bartram, Brown, and Stulz (2012) argue that the stock market volatility of a country can be high due to a favorable business environment, which encourages firms to take risks in that country. For example, Obstfeld (1994) demonstrates that global diversification through market liberalization has a positive effect on expected consumption growth since it shifts the world portfolio from safe, low yield capital, into riskier, high yield capital. On the other hand, factors such as political risk, corruption, and weak protection of equity holders and creditors, which are typically associated with low economic growth (Haidar, 2009; Mo, 2001), impose risks on firms that they cannot shed, which leads to increased stock market volatility (Bartram, Brown, & Stulz, 2012). Acemoglu and Zilibotti (1997) link the degree of market incompleteness to economic growth. They argue that the presence of indivisible projects limits the diversification of the economy and imposes idiosyncratic risk, which slows down capital accumulation due to risk aversion.

Financial theory states that idiosyncratic risk can be eliminated by holding a well-diversified portfolio (Bodie, Kane, & Marcus, 2014, s. 206) and may therefore be of little importance. However, in practice, many investors have large holdings of individual stocks and thus fail to remove the idiosyncratic risk from their portfolio completely. Arbitrageurs, who trade to exploit the mispricing on individual stocks, are also affected by idiosyncratic risk. Increased idiosyncratic risk may increase possible pricing errors and hence create opportunities for the arbitrageurs (Campbell, Lettau, Burton, & Xu, 2001). Another factor contributing to the importance of idiosyncratic risk is its potential to predict excess stock returns. Although Markowitz (1952) argue that rational investors in perfect capital markets diversify completely by holding uncorrelated assets in their portfolio, and traditional asset pricing theories suggest that the only determinant of excess return should be the systematic risk (Black, 1972; Lintner, 1965; Sharpe, 1964), the empirical evidence is ambiguous. Several articles find that idiosyncratic risk is relevant in predicting returns (Goyal & Santa-Clara, 2003; Rehman, Kamal, & Amin, 2017; Spiegel & Wang, 2005; Vidal-García, Vidal, & Khuong Nguyen, 2016), however Angelidis and Tessaromitis (2008) find little evidence in support of this in the

European stock markets. Campbell et al. (2001) also point out that the adequacy of the conventional approximation that a portfolio of 20 or 30 stocks is a well-diversified portfolio in which all idiosyncratic risk is eliminated depends on the level of idiosyncratic risk of the stocks making up the portfolio.

The determinants of volatility have previously been investigated by Bartram, Brown and Stulz (2012), Campbell et al. (2001), Kumari, Mahakud and Hiremath (2017), Papadamou, Sidiropoulos and Spyromitros (2017), among others. In terms of problem formulation and methodology, our thesis lies closest to the article of Bartram, Brown and Stulz (2012). They find that stocks of U.S. firms were more volatile than stocks of comparable foreign firms between 1990 and 2006, and that the difference is mainly related to higher idiosyncratic volatility of U.S. stocks, which they explain with different firm and country characteristics using Fama-MacBeth style regressions. However, since they only investigate how and why U.S. stocks differ from the rest of the world, treated as one group, one cannot draw any conclusions for other specific countries. Since investors have a tendency to allocate a large share of their portfolio to domestic assets (Bodie, Kane, & Marcus, 2014, ss. 916-920; Kilka & Weber, 2000), we believe it is motivated to also investigate the volatility of Swedish stocks in a European perspective, which leads to the following research questions:

1. Does the volatility of Swedish stocks differ from stocks of comparable firms from other European countries?

2. Do the differences in volatility arise from differences in systematic or idiosyncratic risk, and how can the differences in idiosyncratic volatility be explained?

In this thesis, we find that across 3,673 firms during the timespan 2001-2016, Swedish firms have on average lower volatility compared to foreign European firms of similar size, age, and market-to-book value. We decompose total volatility into systematic and idiosyncratic volatility and estimate these risk measures using the Fama-French three-factor model. Our results then indicate that the difference in total volatility is most persistent and evident in idiosyncratic volatility. Further, when we try to explain this difference using several firm and country characteristics in a panel regression model, we find that Swedish firms are likely to have lower idiosyncratic volatility compared to similar European firms due to greater equity market development and less country risk.

The remainder of this thesis proceeds as follows. *Section 2* reviews relevant previous research. *Section 3* presents the data and its sources, *Section 4* discusses the theoretical framework and the theoretical arguments we bring to the analysis, *Section 5* describes our empirical methodology and results, and *Section 6* concludes.

2 Literature review

In this section, we present previous research about the economic determinants of stock market volatility.

Bartram, Brown and Stulz (2012) show that stocks of U.S. firms are more volatile than stocks of comparable non-U.S. firms. They investigate whether the difference is due to a favorable environment for firms to take risks, which they call good volatility, or country-specific forces such as political risk, which is referred to as bad volatility. They estimate the idiosyncratic volatility as the annualized standard deviation of the residuals from the three-factor model suggested by Fama and French (1996) of excess dollar returns, but extend it by using both local and global market, small-minus-big and high-minus-low portfolios. Their estimate of systematic risk is the square root of the difference between total return variance and the idiosyncratic variance. To make the sets of U.S. and non-U.S. firms more comparable, they perform propensity score matching based on firm size, firm age, and market to book ratio. When comparing non-U.S. firms to their matched U.S. firms, they show that non-U.S. firms have lower total risk, and that the difference is mainly attributable to differences in idiosyncratic risk. They then use four different approaches to investigate country and firm specific determinants of the difference in idiosyncratic volatility; two types of Fama-MacBeth style regressions (Fama & MacBeth, 1973) which is their primary method, a single cross-sectional regression of the firms' means, and a panel regression with the Yule-Walker method to account for autocorrelation. They have log-differences in idiosyncratic volatility between matched firms as dependent variable and lagged standardized differences in firm and country specific characteristics as explanatory variables. Their results indicate that idiosyncratic risk increases with equity market development and innovation, and firms' leverage and cash holdings, while it falls with bond market development, capital account openness, and firms' total assets, age, and profitability. From these results, they conclude that the higher idiosyncratic volatility of the United States is associated with factors they would expect to be associated with higher economic welfare. They also discuss the determinants of systematic risk and find that the relations between the explanatory variables and systematic risk are mostly the same as those observed for idiosyncratic risk, with the addition that systematic risk increases with political risk and anti-director index, while they were insignificant for idiosyncratic risk.

Papadamou, Sidiropoulos and Spyromitros (2017) develop a theoretical model showing a positive relationship between stock market volatility and central bank independence. By analyzing 29 countries from 1998 to 2005, they also provide empirical evidence that a high level of central bank independence can increase stock market volatility. They use two different measures of stock market volatility; conditional volatility based on the estimation of a GARCH model and historical volatility. They find that the conditional volatility has a higher mean and standard deviation than the historical volatility. To estimate the relationship between central bank's independence and transparency and stock market volatility, they use panel data methodology, which they motivate by arguments from Wooldridge (2002), stating that panel data control for individual heterogeneity and diminishes problems associated with multicollinearity and estimation bias. Drawing on previous works of Mun (2007), Umutlu, Akdeniz and Aktay-Salih (2010), and Esqueda, Assefa and Mollick (2012), they include as control variables the stock market capitalization to GDP, volatility of quarterly interest rates, foreign equity flows and foreign direct investment flows divided by GDP to measure financial integration, and the value of shares traded over average market capitalization to capture liquidity effects. As macroeconomic factors, they control for real GDP growth and exchange rate volatility. Their findings confirm their theoretical argument of positive effects of central bank independence on stock market volatility, both when only testing the central bank characteristics and when including control variables. The results also indicate that transparency may have a beneficial effect on stock market volatility, but the effects of independence are larger in absolute terms.

Campbell et al. (2001) discover an upward trend in idiosyncratic volatility for U.S. stocks between 1962 and 1997. They also find that market, industry, and firm-level volatility are positively correlated with each other as well as autocorrelated. After performing Granger-causality tests, they suggest that market volatility tend to lead the other volatility series. They also conclude that all three measures increase in economic downturns and lead recessions, and that industry level volatility can be used to forecast economic activity. However, Brandt, Brav, Graham and Kumar (2010) show that the idiosyncratic volatility decreased to pre-1990s levels at the beginning of the 2000s and argue that the upward trend documented by Campbell et al. (2001) was a temporary phenomenon, at least partly driven by retail investors. This is supported by Bekaert, Hodrick and Zhang (2012) who conclude that there are no significant trends in idiosyncratic volatility for non-U.S. developed countries, and state that even though the results of Campbell et al. (2001) are robust to alternative methodologies and tests, they are sensitive to the sample period. Bekaert, Hodrick and Zhang (2012) also show that idiosyncratic volatility is correlated across countries and that the correlations have increased over time.

Kumari, Mahakud and Hiremath (2017) identify firm-specific variables that explain the idiosyncratic risk of Indian stocks between 1996 and 2013. Firstly, they estimate the unconditional idiosyncratic volatility as the standard deviation of the residuals of a five-factor model of excess returns, and the conditional idiosyncratic volatility from an exponential GARCH (1, 1) model. They then specify a panel model with firm-specific characteristics as explanatory variables. Their results show that unconditional idiosyncratic volatility is steady, while the conditional volatility fluctuates over the years and does not follow any trend. Furthermore, Hausman, F, LR, and LM tests all suggest that the fixed effects model is more appropriate than the random effects model for both conditional and unconditional idiosyncratic volatility. Firm size, book-to-market ratio, and cash flow-to-price ratio are significant in determining unconditional idiosyncratic volatility, while size, momentum, and liquidity are significant for conditional idiosyncratic volatility.

3 Data

In this section, we discuss the data and its limitations. The purpose of this section is to inform the reader how we obtain the data, how we use the data, and where the reader can collect the data.

Our initial dataset consists of weekly total returns, market capitalization, and book-to-market value of firms listed in countries located in Europe, and total returns of the countries' stock market indices and Treasury bills. Total return assumes that dividends are re-invested to purchase additional units of the equity. These are collected in Euro from Datastream between 2001 and 2016. We exclude countries that did not have a stock exchange during the whole sample period and countries for which data for all our country characteristics are not available in either of the World Bank, Datastream, or Worldscope databases. This screening leaves us 32 countries, which can be seen in *Table 5-1*. The firms chosen are the ones constituting the largest index in terms of number of stocks for each country. For firms listed on multiple exchanges, we collect the primary listing and drop all secondary listings. Further, we only include the most traded stock when firms have more than one stock issued. This initial dataset includes 3,673 firms and is used for the estimation of 48,555 annual volatilities of the stock returns, which enter into our primary dataset of both firm and country characteristic variables.

The set of firms in the primary dataset is a subset of the firms in our initial dataset. In terms of firm characteristic variables, we also require firm age, market-to-book, and total assets to be non-missing since these variables are used in the matching procedure where each non-Swedish firm is matched to a Swedish firm. This results in a primary data set consisting of 38,913 firm-year observations. The United Kingdom has 4,749 firm-year observations and is the country with the most while Iceland has the fewest with 57 firm-year observations. Sweden has 2,779 firm-year observations. Notable is that the number of firms in our sample has more than doubled during our timespan. In our first observation year, 2001, we have 1,462 firms which increase to 3,248 at the end of our period, 2016. The data is retrieved annually in euros stretching from 1999 to 2016 where data prior to 2001 is used for the profitability variable which is a three-year average and also for the lagged variables used in the matching procedure, see *Section 5.1.2*. The variables we collect together with definitions and the sources used to obtain them are shown in *Table 3-1* and *Table 3-2*.

Variable	Definition	Source
Firm characteristics		
Age	The difference between the year of observation and the year from which Datastream holds information about the firm.	Datastream
Cash & STI	The sum of cash and short-term investments.	Worldscope
Gross income	The difference between sales or revenues and costs of goods sold and depreciation.	Worldscope
Leverage	The sum of total debt and preferred stocks, divided by market capitalization.	Worldscope
Market-to-book value	The ratio of a firm's market value and its book value.	Datastream
Net sales or revenues	Gross sales and other operating revenue less discounts, returns, and allowances.	Worldscope
PPE	Total property, plant, and equipment (net).	Worldscope
Research & Development	All direct and indirect costs related to the creation and development of new processes, techniques, applications, and products with commercial possibilities.	Worldscope
Share zero returns	The share of firm weekly local currency returns in a year equal to zero.	Datastream
Total assets	The sum of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property, plant and, equipment and other assets.	Worldscope
Total debt	The sum of long- and short-term debts.	Worldscope
Total long-term debt	Loans and financial obligations lasting over one year.	Worldscope

Table 3-1 Collected firm characteristics together with their definitions and sources used to obtain them.

Variable	Definition	Source
Country characteristics		
Capital account openness	An index that measures a country's openness to cross-border capital transactions. Higher values indicate more openness.	(Chinn & Ito, 2006)
Capital flows	The sum of inflows and outflows in foreign direct investments and portfolio equity divided by GDP.	World Bank
Corruption	An index between 0 and 10 that measures the corruption in a country's public sector. Higher values indicate less corruption.	Transparency International
Creditor rights	An index between 0 and 4 that measures the participation and rights of creditors. Higher values indicate greater participation and rights of creditors.	World Bank
Disclosure	An index between 0 and 10 that measures the extent to which investors are protected through disclosure of ownership and financial information. Higher values indicate more disclosure.	World Bank
Exchange rate volatility	The annualized standard deviation of weekly exchange rates.	Datastream
Market coverage	The ratio of the number of firms in a country that are in our sample and the total amount of firms in the country.	World Bank
Patents (per million population)	The number of patent applications by residents in the year of interest divided by the population in millions.	Datastream
Political risk	An index between 0 and 7 that measures the political stability. Higher values indicate less political risk.	Oxford Economics
Private bond market (share of GDP)	Private domestic debt securities issued by financial institutions and corporations as a share of GDP.	World Bank
Stock market capitalization (share of GDP)	The ratio of stock market capitalization and nominal GDP.	World Bank
Stock market turnover ratio	The value of domestic shares traded divided by their market capitalization.	World Bank

Table 3-2 Collected country characteristics together with their definitions and sources used to obtain them.

4 Theory

In this section, we present theoretical models and explain their relevance to our research questions. We also discuss theories on determinants of firms' idiosyncratic volatility.

4.1 Fama-French three-factor model

A widely used tool to evaluate financial assets is the Capital asset pricing model, CAPM. However, the CAPM rely solely on the excess market return to describe the excess return of a portfolio or an individual asset. Consequently, The CAPM neglects other factors that may affect the returns. To address this problem, researchers frequently use the Fama and French three-factor model which incorporates two additional factors; the book-to-market ratio and the firm size (Coskun, Selcuk-Kestel, & Yilmaz, 2017). Fama and French (1996) describe that weak firms with persistently low earnings tend to have high book-to-market equity and are more likely to be in financial distress. Further, they also argue that small stocks may be more sensitive to changes in business conditions. Consequently, the book-to-market ratio and the firm size may capture the sensitivity to macroeconomic risk factors. The Fama and French three-factor model is defined in *Equation 1*, where $[E(R_i) - R_f]$ represents the excess return of asset i, which is explained by its sensitivity to the three factors; the excess return on a market index, R_M, the difference between the return on a portfolio of small stocks and the return on a portfolio of big stocks, R_{SMB}, and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks, R_{HML}. (Fama & French, 1996)

$$E(R_i) - R_f = \beta_{iM}[E(R_M) - R_f] + \beta_{iSMB}E(R_{SMB}) + \beta_{iHML}E(R_{HML})$$

Equation 1

Fama and French (1996) use firms' market capitalization and their book-to-market ratio to construct R_{SMB} and R_{HML}. The median value of the market capitalization for the firms determines a Small and a Big group. The Small group consists of the firms with a market capitalization below the median and the Big group consists of the firms with a market capitalization above the median. Further, Fama and French (1996) use the book-to-market ratio to construct three additional groups; Low, Medium and High. The Low group consists of stocks with the bottom 30% book-to-market ratio, the Medium group consists of stocks with the middle 40% book-to-market ratio, and the High group consists of stocks with the top 30% book-to-market ratio. The constructed groups are then intersected to form six value-weighted portfolios: Small/Low, Small/Medium, Small/High, Big/Small, Big/Medium, and Big/High. The returns on the Small, Big, High, and Low portfolios are:

$$R_S = \frac{1}{3}\left(R_{S/L} + R_{S/M} + R_{S/H}\right);\ R_B = \frac{1}{3}\left(R_{B/L} + R_{B/M} + R_{B/H}\right)$$

Equation 2

$$R_H = \frac{1}{2}\left(R_{S/H} + R_{B/H}\right); R_L = \frac{1}{2}\left(R_{S/L} + R_{B/L}\right)$$

Equation 3

Finally, R_{SMB} and R_{HML} are constructed using these portfolios:

$$R_{SMB} = R_S - R_B; R_{HML} = R_H - R_L$$

Equation 4

(Bodie, Kane, & Marcus, 2014, ss. 427-428)

4.2 Risk measures

A firm's total risk can be decomposed into systematic risk and idiosyncratic risk. The latter is a risk specifically associated with the firm while the systematic risk is a risk associated with the overall market. Although the firm-specific risk can be eliminated by adding assets to a portfolio, the systematic risk will always remain (Bodie, Kane, & Marcus, 2014, s. 206). Since the idiosyncratic risk can be diversified, early theoretical models by Sharpe (1964), Lintner (1965), and Black (1972) suggest that the systematic risk is the only determinant of expected excess stock returns. In the Fama and French three-factor model, the systematic variance is given by the variance of the systematic components of the excess returns, i.e. the right-hand side of *Equation 1*. The idiosyncratic variance is then the variance of the excess return that is not explained by the systematic components. The relationship between the total variance, the systematic variance, and the idiosyncratic variance is shown in *Equation 5* (Bodie, Kane, & Marcus, 2014, ss. 426-428).

$$\sigma^2_{Total} = \sigma^2_{Systematic} + \sigma^2_{Idiosyncratic}$$

Equation 5

4.3 Determinants of idiosyncratic volatility

John, Litov and Yeung (2008) present two theories suggesting a positive relation between investor protection and risk-taking at a firm level. Firstly, firms in countries with poor investor protection may have dominant insiders possessing significant cash flow rights and a large share of their wealth invested in the firm they control. Consequently, they may be conservative in their investments and forego risky projects to protect their private benefits. Secondly, stakeholders such as banks and governments have more influence in countries with weak investor protection. These stakeholders often prefer less risky corporate investments and may therefore influence investment policy for their self-interest.

Thesmar and Thoenig (2004) argue that financial development facilitates the access for investors to invest and hence the number of potential investors increases. A wider pool of investors allows for greater risk sharing among the owners and consequently, the firms can adopt riskier and more profitable decisions. Financial development can also ease funding through creditors (Hung & Cothren, 2002). Bartram, Brown and Stulz (2012) argue that the relation between firms' risk-taking and funding through creditors is negative. Their theory is that funding through creditors causes creditors to have a greater influence on firms' investment decisions and may therefore limit their risk-takings.

As mentioned above, financial development may increase the number of investors. Another factor that may affect the number of possible investors is a country's degree of financial liberalization. Umutlu, Akdeniz and Altay-Salih (2010) distinguish between two groups of measures of financial liberalization: restriction based and capital flow based. They describe that an advantage of restriction based measures is that they are a direct depiction of government restrictions. However, the measures are often constructed by binary classifications, and hence they may suffer from accuracy. In contrast to restriction based measures, Umutlu, Akdeniz and Altay-Salih (2010) argue that the strength of capital flow based measures lies in their accuracy of representing the intensity of a country's openness. Their weakness may however be the ambiguous direction of causality between capital flows and stocks' volatility since the volatility could affect the capital flows itself. Umutlu, Akdeniz and Altay-Salih (2010) state that financial liberalization broadens the investor base due to an increased number of foreign investors. However, in contrast to Thesmar and Thoenig (2004), they present an alternative theory suggesting that the increased number of market participants contributes to additional and more precise public information and consequently decreases idiosyncratic risk.

Two factors that seem to be relevant in determining firms' idiosyncratic risk are innovation and growth opportunities. In terms of innovation, Pástor and Veronesi (2009) argue that new technologies are associated with small scale of production and low probability of large-scale adoption. As a result, one may expect firms' idiosyncratic risk to be higher in countries with more innovation. Further, Bartram, Brown and Stulz (2012) suggest that firms with greater growth opportunities possess a higher idiosyncratic risk. Their theory is that there exist more information asymmetries about growth compared to the information asymmetries about assets in place.

Acemoglu, Johnson, Robinson and Thaicharoen (2003) present a theory suggesting that country risk, in particular greater threat of expropriation, increases systematic risk. This theory is extended by Bartram, Brown and Stulz (2012) which further suggest that increased systematic risk due to a greater threat of expropriation decreases the rewards of risk-taking at the firm level. Consequently, one would expect lower idiosyncratic risk for firms listed in countries exposed to a higher risk. Bartram, Brown and Stulz (2012) also present an alternative theory stating that country risk may cause more firm-specific shocks which may be difficult to avoid and hence increase firms' idiosyncratic risk.

Another factor that may be closely related to firms' idiosyncratic risk is cash holdings. One theory is that firms hold more cash as a precautionary motive. To handle negative shocks firms may hold more cash, in particular when access to capital markets is costly (Bates, Kahile, & Stulz, 2009). However, the causality may not be that higher cash holdings cause greater idiosyncratic risk. Rather, firms that take more risks or expect to take more risks in the future may hold more cash (Bartram, Brown, & Stulz, 2012).

4.4 Panel data

An attractive feature of panel data compared with time series or cross-sectional data is that repeated observations of the same units make it possible to analyze changes on an individual level. However, since we repeatedly observe the same units, the standard assumption of independent observations may no longer be appropriate. Hence, routinely computed standard errors for OLS based on the assumption of independent and identically distributed error terms could be misleading, and OLS is likely to be inefficient relative to an estimator that exploits the serial correlation. This is illustrated with a standard linear regression model by Verbeek (2012, ss. 372-386):

$$y_{it} = \beta_0 + \boldsymbol{x}_{it}\boldsymbol{\beta} + \varepsilon_{it}$$

Equation 6

Where $\boldsymbol{x}_{it}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of its corresponding coefficients, β_0 is an intercept, and ε_{it} is an error term, which varies over individuals and time. The OLS estimator is consistent for β_0 and $\boldsymbol{\beta}$ under weak regulatory conditions if $E\{\varepsilon_{it} = 0\}$ and $E\{x_{it}\varepsilon_{it} = 0\}$. The random effects model assumes that $\varepsilon_{it} = c_i + u_{it}$, where u_{it} is assumed to be homoscedastic and serially uncorrelated, and c_i is an unobserved individual-specific effect which is time-invariant and homoscedastic across individuals. Hence, a necessary condition for consistency is that the explanatory variables are uncorrelated with the individual effect, since they otherwise would be correlated with the error term, so $E\{x_{it}\varepsilon_{it} = 0\}$ is violated.

The assumption of zero correlation between the unobserved effects and the explanatory variables may be restrictive. This is addressed in the fixed effects model by including individual-specific intercepts, which capture all time-invariant differences across individuals so that the error term can be assumed to be independent and identically distributed over individuals and time (Verbeek, 2012, ss. 372-386). One can also add a time-specific intercept, λ_t, to capture time effects that are common across individuals. The unobserved individual effects are coefficients on dummies for each individual, while the year effects are coefficients on time dummies (Angrist & Pischke, 2009, ss. 221-227). This gives the following fixed effects model:

$$y_{it} = c_i + \lambda_t + \boldsymbol{x}_{it}\boldsymbol{\beta} + u_{it}$$

Equation 7

Consistency of the above panel data estimators require the explanatory variables to be uncorrelated with the idiosyncratic error in each time period, and standard forms of statistical inference and efficiency properties of standard estimators rely on the assumption of strict exogeneity, that is $E(y_{it}|x_{i1}, x_{i2}, \dots, x_{iT},\ c_i) = E(y_{it}|x_{it}, c_i)$ (Wooldridge, 2010, ss. 287-288). An alternative estimator is the first-difference estimator:

$$\Delta y_{it} = \Delta \boldsymbol{x}_{it}\boldsymbol{\beta} + \Delta u_{it}$$

Equation 8

Where $\Delta y_{it} = y_{it} - y_{i,t-1}$. Consistency requires that $E\{\Delta x_{it}\Delta u_{it}\} = 0$, which is weaker than strict exogeneity since it allows correlation between x_{it} and $u_{i,t-2}$. (Verbeek, 2012, s. 379)

If the assumptions of strict exogeneity and serially uncorrelated and homoscedastic idiosyncratic errors are satisfied, and the model does not actually contain an unobserved effect, then, according to Wooldridge (2010, ss. 299-316), pooled OLS is efficient and its statistics are asymptotically valid. It is still consistent in the presence of an unobserved effect in the error term, provided that it is uncorrelated with the error term. However, the errors will be serially correlated, so inference requires a robust variance estimator. The random effects estimator on the other hand exploits the serial correlation in a generalized least squares framework, and is efficient in the class of estimators consistent under $E\{\varepsilon_{it}|\boldsymbol{x}_i\} = 0$. Furthermore, under the assumptions of homoscedasticity and no serial correlation, the first difference estimator is less efficient than the fixed effects estimator.

5 Empirical analysis

In this section, we present our approach to estimate the risk measures and to match non-Swedish firms to similar Swedish firms. We also present the estimated risk measures, firm and country characteristics, and average differences between the matched pairs. Finally, we motivate our choice of regression model, perform tests to check the assumptions behind our model specification, and analyze the results of our panel regression.

5.1 Econometric approach

5.1.1 Estimating the risk measures

We calculate the yearly total risk for each firm using weekly stock returns data. The total risk is measured as the annualized standard deviation of the weekly excess stock returns. We assume that a firm's return is uncorrelated from one week to another and hence the annualized standard deviation is obtained through *Equation 9*, where *T* indicates the number of weekly observation in the given year (Bodie, Kane, & Marcus, 2014, ss. 133-134).

$$\sigma_{Annual} = \sqrt{T}\sigma_{Weekly}$$

Equation 9

Furthermore, we decompose the total risk into idiosyncratic risk and systematic risk. To fulfill the decomposition, we estimate the yearly idiosyncratic risk for each firm using the time series regression, *Equation 10*, of the Fama and French three-factor model from *Equation 1* (Fama & French, 1996).

$$R_{it} - R_f = \alpha_i + \beta_{iM}\left(R_{Mt} - R_f\right) + \beta_{iSMB}R_{SMB,t} + \beta_{iHML}R_{HML,t} + \varepsilon_{it}$$

Equation 10

We use local Treasury bill rate as risk-free rate to calculate the excess return for each firm as well as the excess return of the market index. We use *Equation 2-4* with the initial dataset where only the returns, book-to-market, and market capitalization is required to be non-missing to construct the R_{SMB} and R_{HML} for each country. Our estimate of the idiosyncratic risk is then the annualized standard deviation of the residuals in *Equation 10*. Once the total risk and the idiosyncratic risk are estimated, we obtain the systematic risk by rewriting *Equation 5* into:

$$\sigma_{Systematic} = \sqrt{\sigma^2_{Total} - \sigma^2_{Idiosyncratic}}$$

Our estimated median total, systematic, and idiosyncratic volatility for each country is shown in *Table 5-1* below, along with the number of firm-year observations with the available data for the matching variables.

Country	Total risk	Systematic risk	Idiosyncratic risk	Firm-year observations
Austria	0.287	0.126	0.247	636
Belgium	0.265	0.113	0.235	1216
Bulgaria	0.348	0.219	0.259	133
Croatia	0.321	0.170	0.261	212
Czech Republic	0.251	0.132	0.184	153
Denmark	0.307	0.124	0.278	1357
Estonia	0.292	0.181	0.224	132
Finland	0.308	0.136	0.270	1276
France	0.333	0.162	0.281	3464
Germany	0.320	0.149	0.279	1487
Greece	0.481	0.236	0.393	1722
Hungary	0.324	0.204	0.235	190
Iceland	0.220	0.125	0.165	57
Ireland	0.344	0.167	0.302	345
Italy	0.324	0.160	0.270	2635
Latvia	0.388	0.198	0.341	99
Lithuania	0.300	0.129	0.279	200
Luxembourg	0.228	0.104	0.198	113
Malta	0.199	0.081	0.179	134
Netherlands	0.310	0.156	0.258	1084
Norway	0.421	0.198	0.353	1350
Poland	0.409	0.175	0.364	2393
Portugal	0.332	0.162	0.289	529
Romania	0.521	0.179	0.478	793
Russia	0.390	0.139	0.322	2134
Slovakia	0.263	0.170	0.210	94
Slovenia	0.313	0.128	0.279	187
Spain	0.301	0.175	0.242	1252
Sweden	0.355	0.177	0.295	2779
Switzerland	0.261	0.116	0.228	2276
Turkey	0.489	0.302	0.351	3732
United Kingdom	0.310	0.163	0.252	4749
Full sample	0.351	0.171	0.290	38 913

Table 5-1: Country level median values of annual total, systematic, and idiosyncratic risk in our initial dataset. The risk measures are derived from data for 2001-2016. The number of firm-year observations in our primary data set is also shown where firms missing data on age, market-to-book ratio, or total assets are excluded.

5.1.2 Propensity score matching

To match Swedish firms with similar foreign firms, we use a similar approach as Bartram, Brown and Stulz (2012), the propensity score matching. The propensity score matching has become increasingly popular by researchers in recent years since it allows comparing firms along multiple dimensions (Verbeek, 2012, ss. 266-267). Propensity score matching is a procedure using two steps. The first step includes an estimation of the propensity scores. The propensity scores are then used, in the second step, to form a matched sample that suffers from less bias. (Svetina, 2012).

In the first step, where we estimate the propensity scores, we use a binary logistic regression where the dependent variable indicates whether the firm is a Swedish or a non-Swedish firm. Non-Swedish firms are coded as one and Swedish firms are coded as zero. Further, we use the same explanatory variables as Bartram, Brown and Stulz (2012). More specifically, we match each Swedish firm to a non-Swedish firm based on the log of total assets, the log of age, and market-to-book value, all of which are lagged by one period. They argue that the explanatory variables and the risk measures should not be determined simultaneously. Therefore, they only use lagged variables and variables that are likely to be exogenous. The regression model is defined in *Equation 11* and describes the conditional probability of being a non-Swedish firm.

$$P\{y_i = 1|\boldsymbol{x}_i\} = \frac{e^{\alpha + \boldsymbol{x}_i \boldsymbol{\beta}}}{1 + e^{\alpha + \boldsymbol{x}_i \boldsymbol{\beta}}}$$

Equation 11

y_i is a binary variable indicating whether the firm is a Swedish or a non-Swedish firm where zero and one represents Swedish and non-Swedish firms respectively. $\boldsymbol{x}_i$ represents a vector consisting of our matching variables and $\boldsymbol{\beta}$ represents a vector consisting of the coefficients corresponding to the explanatory variables. (Verbeek, 2012, ss. 206-208).

Once the propensity scores are estimated we use the nearest neighbor method to match each Swedish firm with a foreign firm, i.e. each Swedish firm is matched with the non-Swedish firm that has the most similar propensity score (Ho, Imai, King, & Stuart, 2011). A problem that may arise when using the nearest neighbor to match the firms is that a Swedish firm may be forced to match a foreign firm even though it is different from all the foreign firms. To address this problem, we impose a caliper restriction where the difference in the propensity scores between the matched firms is not allowed to exceed 0.25 standard deviations of the propensity scores. Matched pairs that do not satisfy this restriction will be dropped from the sample. The number of Swedish firms is fewer than the foreign firms, hence we match each Swedish firm to a foreign firm with replacement. We perform the matching procedure each year since the firms, in terms of our explanatory variables, may change over time.

Table 5-2 below shows the total averages of our firm and country characteristics for the non-Swedish firms and their matched Swedish firms, the difference between them and p-values from weighted t-tests of the differences of firm characteristics. We take the average of the annual observations of each non-Swedish firm, so that each non-Swedish firm appears only once. Swedish firms tend to be less leveraged and have a lower ratio of property, plant and equipment to total assets and a lower share of zero returns. They hold slightly more cash and short-term investments, however the difference is not statistically significant. Swedish firms are on average also more profitable and have a larger ratio of R&D to capital expenditures, but the latter should be interpreted carefully because of its large number of missing observations. None of our matching variables *Age*, *Market-to-book value*, or *Total assets* differs significantly; this would otherwise have been an indicator of poorly performed matching.

On the country level, our results indicate that Sweden has more developed equity and credit markets than the average of other countries in our sample, weighted by the number of matched firms; the differences in *Stock market capitalization*, *Stock market turnover,* and *Private bond market* are all negative. The negative difference in patents per million of population suggests that Sweden is more innovative. The variables representing financial openness on the other hand give somewhat contradictory results; Sweden has fewer capital restrictions compared to the other countries in our sample, but the amount of foreign capital flows to GDP is smaller. The negative differences in *Corruption* and *Political risk* indicate that Sweden has less country risk, but shareholder protection is worse in terms of *Creditor* *rights* and *Disclosure*. The Swedish exchange rate is more volatile, which is expected since many countries in our sample start using the Euro at the beginning of the sample period. The *Market coverage* variable shows that we have a larger share of all listed Swedish stocks in our sample than we do in the other countries on average. Finally, one should keep in mind that the differences on the country level depend on the weighting and the location of the matched firms. It follows that they should not be interpreted as actual differences in country ability or development and they are therefore not very interesting by themselves. They will however be useful for explaining and interpreting the determinants of the differences in volatility between Swedish and comparable non-Swedish firms.

Variable	Non-Swedish	Swedish	Difference	P-value	
Firm-specific variables					
Age (log)	2.545	2.551	-0.007	0.171	
Cash & STI / Total assets	0.129	0.131	-0.001	0.221	
Debt maturity	0.565	0.648	-0.084	<0.001	***
Leverage	0.370	0.323	0.047	<0.001	***
Market-to-book value	3.096	2.714	0.382	0.328	
PPE / Total assets	0.288	0.238	0.050	<0.001	***
Profitability	0.081	0.280	-0.199	<0.001	***
R&D share	0.320	0.503	-0.183	<0.001	***
Share zero returns	0.096	0.051	0.045	<0.001	***
Total assets (log)	13.068	13.086	-0.018	0.325	
Country-specific variables					
Capital account openness	1.771	2.374	-0.603		
Capital flows	0.115	0.097	0.018		
Corruption	6.424	9.108	-2.684		
Creditor rights	2.059	2.000	0.059		
Disclosure	6.582	5.894	0.688		
Exchange rate volatility	0.051	0.066	-0.015		
Market coverage	0.465	0.640	-0.175		
Patents (log)	4.877	5.572	-0.696		
Political risk	5.369	6.340	-0.971		
Private bond market	0.296	0.319	-0.023		
Stock market capitalization	0.693	1.117	-0.424		
Stock market turnover	0.838	1.093	-0.255		

Table 5-2: Weighted averages of firm and country characteristics for non-Swedish firms and the matched Swedish firms, their average differences, and p-values from weighted t-tests of the differences. The asterisks denote the statistical significance of the tests. (*) indicates significance at the 5% level, (**) indicates significance at the 1% level, and (***) indicates significance at the 0.1% level.

Figure 5-1 and *Table 5-3* below show the yearly average total, systematic and idiosyncratic risk for non-Swedish firms and their matched Swedish firms, the differences between the two and the p-values from weighted t-tests of the differences. The differences are positive for all years in our sample period except 2002, which indicate that stocks of Swedish firms are less volatile than stocks of comparable European non-Swedish firms. The p-values show that the differences are statistically significant in all years except 2001 and 2011. For systematic risk, the difference between Swedish and non-Swedish firms is positive for most years, but fluctuates around the x-axis. The difference in idiosyncratic risk on the other hand remains positive after 2003, indicating that stocks of Swedish firms have less idiosyncratic risk than stocks of comparable European non-Swedish firms except for the two first years of our sample period. The p-values show that the differences in idiosyncratic risk are statistically significant for all years in the sample period except 2003. Since Swedish firms tend to both have lower systematic risk and idiosyncratic risk, we cannot draw any clear conclusions of whether the tendency of lower total volatility is due to differences in systematic or idiosyncratic risk. However, the difference in idiosyncratic risk is more evident and persistent over the sample period. We therefore proceed by investigating how the differences in idiosyncratic risk can be explained.

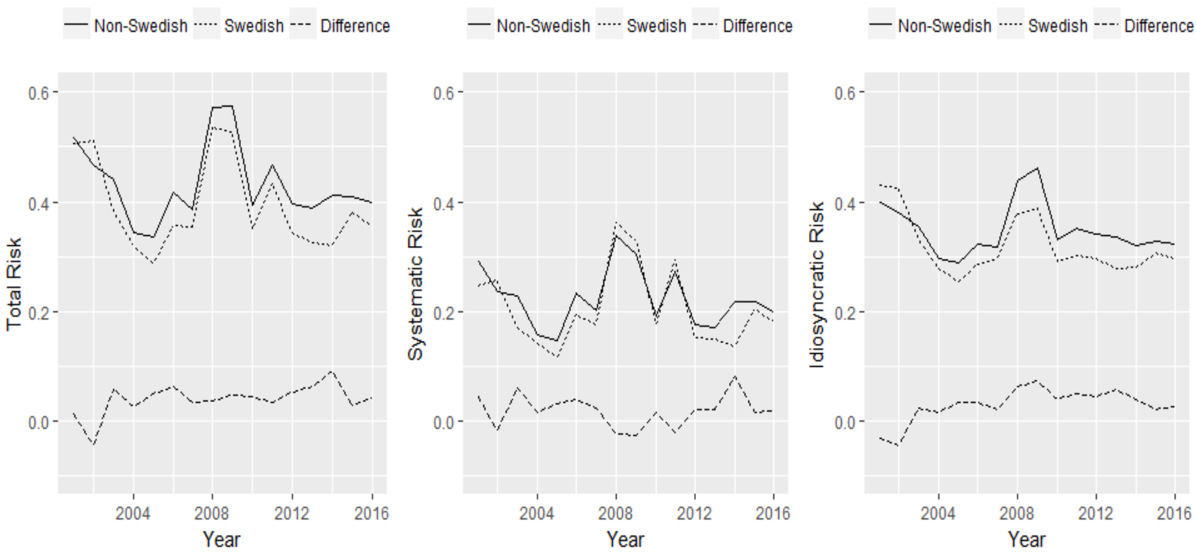

Figure 5-1: Estimates of annual averages of total, systematic and idiosyncratic risk for non-Swedish and Swedish firms and annual average differences of the risk measures for Swedish firms and matched non-Swedish firms between 2001 and 2016.

Year	Total risk					Systematic risk					Idiosyncratic risk				
	Non-Swedish	Swedish	Diff	P-value		Non-Swedish	Swedish	Diff	P-value		Non-Swedish	Swedish	Diff	P-value	
2001	0.518	0.505	0.013	0.349		0.292	0.247	0.045	<0.001	***	0.398	0.430	-0.032	<0.001	***
2002	0.467	0.507	-0.040	<0.001	***	0.236	0.261	-0.025	0.001	**	0.381	0.419	-0.038	<0.001	***
2003	0.442	0.393	0.049	<0.001	***	0.228	0.172	0.056	<0.001	***	0.354	0.340	0.014	0.083	
2004	0.344	0.324	0.020	0.012	*	0.157	0.147	0.010	0.046	*	0.295	0.280	0.015	0.019	*
2005	0.335	0.290	0.045	<0.001	***	0.148	0.117	0.031	0.007	**	0.289	0.258	0.031	<0.001	***
2006	0.418	0.356	0.062	0.020	*	0.233	0.197	0.036	0.160		0.322	0.285	0.037	<0.001	***
2007	0.387	0.357	0.030	0.006	**	0.201	0.180	0.021	0.013	*	0.318	0.299	0.019	0.007	**
2008	0.572	0.537	0.035	<0.001	***	0.338	0.360	-0.022	<0.001	***	0.440	0.382	0.058	<0.001	***
2009	0.574	0.538	0.036	0.078		0.303	0.336	-0.033	0.075		0.461	0.397	0.064	<0.001	***
2010	0.393	0.350	0.043	<0.001	***	0.190	0.177	0.013	0.003	**	0.330	0.290	0.040	<0.001	***
2011	0.470	0.434	0.036	0.111		0.275	0.295	-0.020	0.374		0.353	0.300	0.053	<0.001	***
2012	0.396	0.341	0.055	<0.001	***	0.174	0.152	0.022	<0.001	***	0.342	0.294	0.048	<0.001	***
2013	0.388	0.327	0.061	<0.001	***	0.170	0.151	0.019	<0.001	***	0.335	0.279	0.056	<0.001	***
2014	0.411	0.321	0.090	<0.001	***	0.218	0.138	0.080	<0.001	***	0.319	0.280	0.039	<0.001	***
2015	0.409	0.379	0.030	<0.001	***	0.218	0.205	0.013	0.003	**	0.329	0.305	0.024	<0.001	***
2016	0.399	0.354	0.045	<0.001	***	0.200	0.180	0.020	0.076		0.324	0.295	0.029	<0.001	***

Table 5-3: Annual averages of estimated total, systematic, and idiosyncratic risk for non-Swedish firms and their matched Swedish firms, their average differences, and p-values of weighted t-tests of the differences. The asterisks denote the statistical significance of the tests. (*) indicates significance at the 5% level, (**) indicates significance at the 1% level, and (***) indicates significance at the 0.1% level.

5.1.3 Regression model

As discussed in the literature review, previous research suggests different methods to estimate determinants of idiosyncratic volatility. Bartram, Brown and Stulz (2012) use both Fama-MacBeth style regressions, single cross-section regressions of firm averages, and weighted least-squares panel regressions. Papadamou, Sidiropoulos and Spyromitros (2017), Kumari, Mahakud and Hiremath (2017), Umutlu, Akdeniz and Altay-Salih (2010), and Irvine and Pontiff (2009) all use panel data methods, which seems to be the most common approach. Some of its advantages are that it controls for individual heterogeneity and diminishes problems associated with multicollinearity and estimation bias (Wooldridge, 2002). Furthermore, the results of Nijman and Verbeek (1990) indicate that a panel data set will typically yield more efficient estimates than a series of cross-sections with the same number of observations when exogenous variables are included and one is interested in the parameters that measure the effect of those variables. Fama-MacBeth style regressions have become popular in dealing with large panel data sets in empirical finance applications. Its properties are discussed by Verbeek (2012, ss. 392-394), who argue that the procedure is appealing thanks to its simplicity and that its procedure computes a correct, heteroscedasticity-consistent covariance matrix, resulting in appropriate t-tests. However, the approach is only appropriate if it can be assumed that the parameters of interest are time-invariant and if the error terms are not serially correlated. The standard errors are biased in the presence of a firm effect in the error term or other forms of serial correlation. Another drawback is errors-in-variable issues arising since the explanatory variables first have to be estimated. The alternative method of Bartram, Brown and Stulz (2012) of using a single cross-sectional regression of firm averages has the advantage of eliminating the issue of serial correlation, but at the cost of not making use of the time-wise changes in country and firm characteristics.

Based on the above arguments, we proceed with the panel data approach to explain the differences in idiosyncratic volatility between Swedish and non-Swedish firms with the firm and country characteristics whose theoretical relationships with idiosyncratic volatility we motivate in *Section 4.3*. We use *Creditor rights* and *Disclosure* to represent the degree of investor protection, and let *Stock market capitalization* and *Stock market turnover* proxy for equity market development, while *Private bond market* proxy for credit market development. We include *Capital account openness* as a restriction based measure of financial liberalization, and *Capital flows* as a flow based measure. As indicators of country risks, we use *Corruption* and *Political risk*. Bartram, Brown and Stulz (2012) state that firms acquire growth opportunities through research and development, and find a statistically significant positive relation between idiosyncratic risk and the research and development share, defined as the ratio between costs related to research and development and capital expenditures. They also argue that firms with a lower ratio of property, plant and equipment to total assets possess greater growth opportunities. We therefore include *R&D share* and *PPE / Total assets* as indicators of growth opportunities. We use *Patents (log)*, that is the natural logarithm of the number of patents per million of population as indicator of innovation within countries, and *Cash & STI / Total assets* to measure the firms' cash holdings. We also include *Leverage*, *Debt maturity*, *Profitability*, and *Exchange rate volatility* as control variables based on previous research. The existing literature provides conflicting results on the relation between idiosyncratic risk and leverage. Brown and Kapadia (2007) and Bartram, Brown and Stulz (2012) find a positive relation between idiosyncratic risk and leverage whereas the results of Brandt et al. (2010) indicate the opposite. Further, Fink, Fink, Grullon and Weston (2010) use the leverage as a control variable when they investigate what drove the increase in idiosyncratic risk during the internet boom. For *Debt maturity* and *Profitability*, Bartram, Brown and Stulz (2012) present results indicating a negative effect of both variables on firms' idiosyncratic risk. We measure *Profitability* as the three-year average of the ratio between gross income and net revenues and measure *Debt maturity* as the ratio between long-term debts and total debts. Mun (2007) argues that investing in foreign stock markets entails exposure to exchange rate risk, and empirically confirms a positive relationship between foreign exchange rate volatility and stock market volatility for most countries except the U.S.

Finally, we also include *Share zero returns* to control for liquidity effects, and *Market coverage* to control for selection bias. Most variables are expressed as ratios to make them comparable across countries, their full definitions and sources are explained in *Table 3-1* and *Table 3-2*. Following Bartram, Brown and Stulz (2012), we model the log-differences in idiosyncratic volatility between non-Swedish firms and their matched Swedish firms with standardized differences in firm and country characteristics as explanatory variables, which allows us to interpret the coefficients as the marginal effect of a one standard deviation change in the explanatory variable.

5.1.4 Panel tests and model specification

As described in *Section 4.4*, the choice of estimator relies on the assumptions we make of the potential unobserved effects. As guidance of which assumptions seem most reasonable, we use a number of tests suggested in previous literature. Firstly, we use the test derived by Wooldridge (2010, ss. 299-300) to check for the presence of both unobserved time and individual effects, and hence if pooled OLS is applicable. While it has the advantage of not assuming any particular distribution of u_{it}, Wooldridge's test relies on large-T asymptotics when testing for time effects, so we complement it by also performing the Lagrange multiplier test of Breusch and Pagan (1980) for time-specific effects. To investigate if our explanatory variables are correlated with the potential individual effects, we conduct the test suggested by Hausman (1978), which tests if the fixed effects and random effects estimators are significantly different. Since the random effects estimator is consistent (and typically efficient) under the null hypothesis of zero correlation only, a rejection would suggest that the fixed effect estimator is more appropriate, even though this interpretation should be used with caution, as pointed out by Guggenberger (2010). To test the assumption of strict exogeneity, we apply the test described by Wooldridge (2010, ss. 321-322), which uses the fact that the fixed effect and the first difference estimators have different probability limits if u_{it} and x_{is} are correlated for any t and s, and directly compare $\widehat{\boldsymbol{\beta}}_{FE}$ and $\widehat{\boldsymbol{\beta}}_{FD}$ via a Hausman (1978) test.

The assumption of strict exogeneity and the exclusion of time-invariant explanatory variables are sufficient for consistency of the fixed effects estimator. However, even though the firm-specific effects are moved out of the error term, it may still be serially correlated, which would lead to an improper variance matrix estimator (Wooldridge, 2010, ss. 310-311). We therefore apply the tests proposed by Wooldridge with the null hypothesis $\gamma = -1/(T-1)$, where $\gamma = Corr(\ddot{u}_{i,T-1}, \ddot{u}_{i,T})$, and $\ddot{u}_{it} = u_{it} - \bar{u}_i$ are the time-demeaned errors which are negatively correlated under the null hypothesis that the idiosyncratic errors, u_{it}, are uncorrelated. Another issue in panel data studies with potential implications on parameter estimation and inference is the possibility that individuals are interdependent (Sarafidis & Wansbeek, 2012). Under the assumption that the cross-sectional dependence is caused by the presence of common factors, which are unobserved but uncorrelated with the included regressors, the standard fixed effects and random effects are still consistent, although not efficient, and the estimated standard errors are biased (De Hoyos & Sarafidis, 2006). To test for cross-sectional dependence, we apply the CD test proposed by Pesaran (2004), which is appropriate for our data with small T and large N, to test the null hypothesis $cov(u_{it}, u_{jt}) = 0\ for\ i \neq j$.

The results of the Wooldridge, Breusch-Pagan, Hausman, and Pesaran tests are shown in *Table 5-4* below. We strongly reject the null hypothesis of no unobserved individual effects, and while the Wooldridge test for time-specific effect gives a p-value just above 5 %, the Breusch-Pagan test clearly indicates that there is a time-specific effect. We also reject the null hypothesis of zero correlation between the explanatory variables and the individual effects. The Hausman test for strict exogeneity gives us no indication that the assumption of strict exogeneity is violated, and the same holds for the Wooldridge test of serially uncorrelated errors. However, the Pesaran CD test implies that the errors may be cross-sectionally dependent. According to Sarafidis and Wansbeek (2012), the most classic model of cross-sectional dependence is the SUR approach, due to Zellner (1962). However, its assumed asymptotics are fixed N and $T \to \infty$, and the standard SUR is not feasible for $N > T$, as in our model. With $N > T$, Sarafidis and Wansbeek (2012) instead suggest imposing the restriction that there exist clusters of individuals that are arbitrarily correlated although the clusters themselves are unrelated, which gives rise to a cluster-specific SUR approach. It is then possible to estimate a fixed effects model with a robust estimate of the residual covariance matrix under arbitrary cross-sectional dependence within individual clusters. This approach is known as "cluster-specific" standard errors, and is described in Beck and Katz (1995), Cameron and Trivedi (2005, ss. 697-740), and Cameron, Gelbach and Miller (2008).

Test	Null hypothesis	Test statistic	P-value
Wooldridge	No individual-specific effect	7.374	< 0.001 ***
Wooldridge	No time-specific effect	1.943	0.052
Breusch-Pagan	No time-specific effect	195.08	< 0.001 ***
Hausman	Zero correlation between explanatory variables and individual effects	67.63	< 0.001 ***
Hausman	Strict exogeneity	21.282	0.442
Wooldridge	Serially uncorrelated idiosyncratic errors	0.054	0.816
Pesaran CD	Cross-sectional independence	2.51	0.012 *

Table 5-4: Null hypothesis, test statistics, and p-values of Wooldridge, Breusch-Pagan, Hausman, and Pesaran tests. The asterisks denote the statistical significance of the tests. (*) indicates significance at the 5% level, (**) indicates significance at the 1% level, and (***) indicates significance at the 0.1% level.

Based on the above and similar to Papadamou, Sidiropoulos and Spyromitros (2017), we choose the fixed effects model and address possible cross-sectional dependence by applying panel-corrected standard errors as described in Beck and Katz (1995), which takes into account the contemporaneous correlation of errors (and perforce heteroscedasticity). We include both the firm-specific and time-specific effects to account for unobservable time-invariant firm-characteristics as well as possible common shocks that affect all firms, as implied by the Wooldridge and Breusch-Pagan tests. According to Verbeek (2012, ss. 377-379), the fixed effects model explains differences "within" individuals, that is to what extent y_{it} differs from $\bar{y}_i$, and not why $\bar{y}_i$ differs from $\bar{y}_j$. The parametric assumptions about β impose that a change in x has the same effect, regardless of whether it is a change between periods or individuals. Our econometric model is then given by:

$$y_{it} = c_i + \lambda_t + \boldsymbol{x}_{it}\boldsymbol{\beta} + u_{it}$$

Equation 12

Where y_{it} are log-differences in idiosyncratic volatility between non-Swedish firms and their matched Swedish firms, c_i is the firm-specific intercept, capturing all time-invariant differences across firms, and λ_t is a time-varying intercept. $\boldsymbol{\beta}$ is the vector of the explanatory variables' corresponding coefficients, and u_{it} is the error term. $\boldsymbol{x}_{it}$ is the vector of standardized differences of our firm and country-specific variables described in *Section 5.1.3* with some adjustments that follow from our choice of estimator; the variable *Cash* may depend on past values of y as mentioned in *Section 4.3*, we therefore choose to omit it from our final model to avoid violating the exogeneity assumption. The variable *Creditor rights* does not have enough time variation and is therefore also dropped. We also omit the variable *Corruption* since we find it to be highly correlated with both *Political risk* and *Patents*. To avoid losing a large share of our sample due to the many missing observations in *R&D share*, we follow Bartram, Brown and Stulz (2012) and set them to zero. We also run the regression without the *R&D share* variable to check that our other results are not affected too drastically from this adjustment.

5.2 Results of panel regression

Our estimated coefficients and corresponding p-values from our panel regression are shown in *Table 5-5*. The estimated coefficient for *Disclosure* is positive, although not statistically significant. Thus, the result neither supports nor rejects the theory of a positive relation between investor protection and risk-taking at firm level caused by dominant insiders protecting their private benefits by avoiding risky projects. The estimated coefficient for *Private bond market* is close to zero and insignificant indicating that the credit market development may not influence firms' idiosyncratic volatility in our sample. The estimate for *Stock market capitalization* is positive and significant while the coefficient for *Stock market turnover* is close to zero and insignificant. This could indicate a negative relation between equity market development and firms' risk-taking. Therefore, this result does not support the theory where a wider pool of investors allows for greater risk sharing among the owners and thus riskier decisions may be adopted by the firms. It may however be in line with the idea where increased number of market participants contributes to additional and more precise public information and consequently decreases firms' idiosyncratic risk. Further, the coefficients for *Capital account openness* and *Capital flows* are insignificant where the coefficients are ambiguous and close to zero. This indicates that a country's openness does not affect the degree of risk-taking at the firm level in our sample. The theories where countries' innovation and firms' growth opportunities have positive relation to firms' idiosyncratic risk could be applicable in our sample. *Patents (log)*, *PPE / Total assets*, and *R&D share* are all significant where the coefficients for *Patent (log)* and *R&D share* are positive and the coefficient for *PPE / Total assets* is negative. Hence, idiosyncratic risk increases with innovation and growth opportunities, which supports the theory of Pástor and Veronesi (2009). The coefficient for political risk is significant and negative. Hence, it may not be the case that the firms listed in countries exposed to a higher risk are more risk-averse. It could rather be that country risk causes more firm-specific risk that may be difficult for firms to shed. The estimated coefficients for *Debt maturity*, *Leverage*, and *Profitability* are all positive and significant indicating a positive relationship to firms' idiosyncratic volatility. Further, the estimated coefficient for *Exchange rate volatility* is negative and therefore has the opposite sign to the findings by Mun (2007). Although our p-value for the estimated *Exchange rate volatility* is 0.062, one explanation to the opposite sign could be that Mun (2007) examines the relationship between exchange rate volatility and total risk. Thus, it is possible that the firms' systematic risk increases as the exchange rate volatility increases while the firms' idiosyncratic risk decreases with an increased exchange rate volatility. In terms of *Share zero return* the estimated coefficient is negative and significant. This indicates that the liquidity of the stock has a positive relation to firm-specific volatility. Finally, the result shows that the coefficient for *Market Coverage* is close to zero and insignificant.

Variable	Coefficient	P-value
Firm-specific variables		
Debt maturity	0.008	0.022 *
Leverage	0.036	< 0.001 ***
PPE / Total assets	-0.025	< 0.001 ***
Profitability	0.014	0.004 **
R&D share	0.109	< 0.001 ***
Share zero returns	0.037	< 0.001 ***
Country-specific variables		
Capital account openness	-0.003	0.884
Capital flows	0.003	0.571
Disclosure	0.018	0.362
Exchange rate volatility	-0.019	0.062
Market coverage	0.001	0.929
Patents (log)	0.040	0.041 *
Political risk	-0.086	0.015 *
Private bond market	0.004	0.868
Stock market capitalization	-0.090	< 0.001 ***
Stock market turnover	0.001	0.878
Model summary statistics		
Number of observations	23792	
Cross-sections included	2896	
Periods included	16	
Adjusted R^2	0.146	

Table 5-5: Estimated coefficients and p-values of standardized firm- and country-specific variables from panel regression of log-differences in idiosyncratic volatility, and summary statistics for the regression. The asterisks denote the statistical significance of the coefficients. (*) indicates significance at the 5% level, (**) indicates significance at the 1% level, and (***) indicates significance at the 0.1% level.

As shown in *Table 5-2*, Sweden is more innovative in terms of patents per million of population compared to our weighted average of other European countries. Therefore, we find it unlikely that the lower idiosyncratic volatility of Swedish stocks would be explained by differences innovation, since the relation between them is positive. The same reasoning holds for growth opportunities; idiosyncratic risk depends positively on growth opportunities as explain above, but since we in *Section 5.1.2* conclude that Sweden has more growth opportunities, i.e. higher *R&D share* and lower *PPE / Total assets*, our overall results contradict growth opportunities as explanation. Sweden also has less country risk (higher political risk index), which our regression results suggest decreases idiosyncratic volatility. Hence, the theory provided by Bartram, Brown, Stulz (2012), that higher country risk causes more firm-specific shocks that are difficult to avoid, could explain why stocks of non-

Swedish firms have higher idiosyncratic risk. Finally, Sweden also has a more developed equity market, which according to our regression results also decreases idiosyncratic volatility. Umutlu, Akdeniz and Altay-Salih (2010) suggest that increased number of market participants contributes to increased accuracy and availability of public information, which decreases the idiosyncratic risk. This could also be a valid explanation for the lower idiosyncratic risk of Swedish firms.

6 Conclusions and further research

In this section, we present our conclusions of the results and discuss their implications. We also discuss limitations of the thesis and provide some proposals for further research.

We find that stocks of Swedish firms have lower volatility than stocks of comparable European firms. Our findings indicate that both the systematic and idiosyncratic volatility are lower for Swedish firms, but the difference is more apparent and persistent for idiosyncratic volatility. Furthermore, we find that the difference in idiosyncratic volatility is mainly explained by higher equity market development and less country risk. One implication of the lower idiosyncratic volatility of Swedish stocks is that arbitrage opportunities from pricing errors that arise from idiosyncratic risk are more substantial outside of Sweden. Another implication is that the number of assets that are required to approximate a well-diversified portfolio is lower when the investor holds stocks of Swedish firms than stocks of comparable European firms. Idiosyncratic volatility can be high due to a favorable business environment, which encourages firms to take risk in that country. Alternatively, it can be high due to factors that are associated with low economic growth, such as political risk and corruption, weak protection of equity holders and creditors, or low development of financial markets. Our findings suggest that the main reasons for the lower idiosyncratic risk of Swedish stocks are absence of factors that are associated with low economic growth.

We believe that the main limitations of our thesis are related to the collection of data. Firstly, not all firms are included in the Datastream database. Secondly, the availability of data for the firm-specific variables we require to match firms is higher for large companies. The estimated market coverage in our primary dataset of matched firms is 64 % for Sweden, and the weighted average for non-Swedish countries is 46.5 %. When we bring this primary dataset to the regression model, we lose about 38 % of the firm-year observations in our primary dataset due to missing values in our explanatory variables.

Although our results indicate that the difference in total volatility between Swedish firms and comparable foreign European firms is more evident and persistent in idiosyncratic volatility, there seems to be a difference in systematic volatility as well. Bartram, Brown and Stulz

(2012) show that many of the relations between their explanatory variables and systematic volatility are the same as for those they observe for idiosyncratic volatility. However, they also point out some important differences. Consequently, it could be of interest for future research to examine the differences in systematic volatility between Swedish firms and comparable foreign European firms. Further, one could also expand the study by comparing Swedish firms to the rest of the world. If so, it is likely that the firms are more dissimilar and hence one may want to include additional variables in the matching procedure to obtain a sample suffering from less bias. One could also go in the opposite direction and perform the analysis on industry level within a country.

7 References

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