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Authors:
Radu Mihai Milu
Sandra Li Gustavsson

Supervisor:
Hossein Asgharian

Merton's Model Explaining CDS Spreads

- a panel data study of OMX Stockholm traded firms

Abstract

Credit risk arises in almost all financial activities. One way to hedge and trade risk is to use Credit Default Swaps that act like an insurance against credit events. The value of the CDS is related to the probability of the reference entity defaulting. In this paper we aimed to determine how well the variables implied by the Merton model explain the CDS spread. A panel data study of 16 companies belonging to the OMX Stockholm equity index shows that the variables have limited explanatory power. An increasing stock return is narrowing the credit default swap spread, but the time dummies account for most of the variation.

Key Words: Credit Risk, Credit Default Swap, CDS spread, Merton model, OMX Stockholm

1. Introduction

In 2008 we faced the starting point of the worst global financial crisis since the 1930s. Many financial institutions went bankrupt during the crisis and many more would have done so if governments hadn't bailed them out. Gregory (2010, p. xxi) argues that the key driver of the credit crisis was the deficiency of a proper evaluation of default probability and credit exposure. Credit risk can be defined as the risk of loss stemming from a counterparty failing to fulfill its obligations. It arises in almost all financial activities and accounts for the major source of risk for most commercial banks (Byström 2005). To not endanger the stability of the financial system it is crucial to manage the credit risk exposure of financial institutions.

One way to evaluate the credit risk exposure is to use credit ratings that mirror the creditworthiness of firms. Credit rating agencies have though been criticized for being slow to react to market events and too reluctant to downgrading, which is why they are seen as one of the key contributors to the financial crisis (Katz, Munoz & Stephanou 2009). Another way to assess the credit risk is to use accounting based models that are based on historic accounting data, backward looking information, which is infrequently updated. Neither of these measures generates meaningful interpretations in the sense of probability of default or loss given default (Byström 2003). Many people argue it is more forward-looking using marked-based indicators such as share price and credit default swap spreads (see for instance Katz, Munoz & Stephanou 2009).

The Merton model is a well-known marked-based model, well used for evaluating the credit risk of a company. Since stock market data is used to estimate probability of default it is a continuous credit monitoring process that should serve as an early warning protection against changing credit quality (Crosbie & Bohn 2003). Merton characterizes the firm's equity and debt as options issued on its assets and the probability of default is a function of the firm's stock price, stock price volatility and leverage ratio (Byström 2005).

The derivatives market grew rapidly in the beginning of the 21st century as financial institutions used the derivatives as a way to manage risk (Gregory 2010, p. xxi). Credit Default Swaps (CDSs) are the most widely traded kind of credit derivative contracts, invented by JPMorgan bankers in the mid-'90s. The purpose was to hedge and trade credit risk. By removing the risk from the books they were able to free the capital reserves kept by federal law. Credit default swaps act like an insurance against the risk of a credit event occurring to the underlying entity. The seller receives a stream of premium payments, also known as the CDS spread, and is therefore obliged to pay the buyer if a credit event occurs (Philips 2008). The value of the CDS is hence related to the probability of the reference entity defaulting. The spread works as an indicator of distress and a source of information for banks and regulators (Weistroffer 2009).

With the crisis fresh in mind financial risk management is a hot topic today; the implementations of the Basel III regulations have started for the financial firms and the non-financial corporations are investing more resources into risk management. The credit default swaps have great power in determining the market-implied probability of default (Simkovic & Kaminetzky 2011), but there is of importance for risk managers to understand the drivers behind the risk measure. Understanding the determinants of the CDS spreads will help assessing the credit worthiness of individual corporations as well as the stability of the whole financial system.

This paper will examine how well the Merton theory can explain the CDS premium. We use a streamlined version of the model implemented by Hans Byström and apply it on Swedish stock market data. The spread is determined by the probability of default of the underlying entity and the Merton model is suggesting that this probability is determined by stock price, stock volatility and leverage. The purpose of this paper is hence to determine: *how well do the Merton-implied variables; stock price, stock price volatility and leverage ratio, explain the change in the credit default swap spread?*

Using these Merton-implied variables we perform a panel data study of 59 months for 16 companies[1] belonging to the OMX Stockholm equity index. The small sample is due to lack of CDS data. To control for company specific and time specific variation we include dummy variables for the firms and months.

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[1]Assa Abloy, Atlas Copco, Electrolux, Ericsson, Handelsbanken, Investor, Nordea, SCA, Scania, SEB, Securitas, SKF, Swedbank, Swedish Match, Teliasonera, Volvo

The rest of the paper is organized as follows. In the next section we present earlier studies that have covered the subject and how we aim to contribute to this literature. After that the theoretical framework is presented followed by data and descriptive statistics. Thereafter we declare the methodology and the regression model we have chosen. These sections are followed by result and discussion and finish off with the conclusion. The appendix is to be found at the end of this paper where most of the tables and figures are presented.

2. Previous research

There have been various researches on this subject before, but there is no univocal result. The previous studies are, like ours, based on credit risk pricing theories like the Merton model.

Some studies show a weak correlation between the theory-implied determinants and the credit default swaps, while others find the variables have great power in determining the premium. Hull, Nelken and White (2004) used credit default swap spread data to test whether their proposed alternative Merton model provides a superior explanation of observed credit spreads relative to the traditional model. This model is using implied volatilities of options issued by the company to estimate the parameters. There seems to be a positive relationship between the observed spreads and the model predictions stemming from both models, but their proposed version outperforms the traditional Merton model.

Bharath and Shumway (2004) used American stock data to examine how well the KMV-Merton model predicts default. They find that the model is only weakly correlated with implied default probabilities from CDS spreads. The KMV-Merton probability is hence a somewhat useful forecaster of default, but not a satisfactory statistic for default. A much simpler model alternative is also proposed which performs rather well as a default statistic.

Afik, Arad and Gali (2012) offered a specification that performs better than the one proposed earlier by the two authors in 2008. They tried to enhance Merton’s model default probability by comparing the area under the curve of receiving operating characteristic and use non-parametric tests to measure statistical difference between these curves. Their conclusion is that a simplified Merton model performs better than more complex ones used before them.

Ericsson, Jacobs and Oviedo (2004) also investigated the relationship between CDS spreads and theoretical determinants of default risk. These determinants were the riskless interest rate, firm leverage and volatility. The variables are found to be statistically and economically significant, but depend on the econometric method. The explanatory power is larger for the levels of the credit default swap premium than for the changes in the premium.

Abid and Naifar (2006) try to explain the determinants of CDS spreads by using variables such as credit rating, maturity, risk free interest rate, slope of the yield curve and equity volatility. The majority of these variables, originating in the credit risk pricing theories, are significant both statistically and economically, but credit rating turned out to be the most determinant of CDS spreads.

Byström (2005) studies the European iTraxx CDS index market and finds that both current and lagged stock returns explain much of the variability in credit default swap spreads. CDS spreads tend to widen (narrow) when stock prices fall (rise). The stock index return volatility is discovered to be significantly positively correlated with the CDS index spreads, indicating the importance of stock volatility for probability of default calculations.

Our contribution to the already existing literature will be a study based on Swedish stock market data, to our knowledge this has not been done before. The time period covered by the data is highly interesting since it contains observations from the recent recession as well as the recovery of the economy. Most previous studies on the subject were performed before the great financial crisis. We provide a study based on the streamlined version of the Merton model implemented by Hans Byström (2003) and us knowingly this specific implementation has not acted as theoretical basis for the credit default swap spread analysis before.

3. Theoretical framework

3.1 Credit risk and default probabilities

Everyone involved in financial activities is subject to credit risk, i.e. the risk that the counterparty fails to fulfill its financial contracts. There is an uncertainty surrounding a company's ability to make the required payments on their debt obligations. To compensate lenders and investors for the exposure to default risk, firms are charged a rate of return that corresponds to the debtor's level of default risk. The default probability is mainly determined by three elements: *Market value of assets* is a measure of the company's outlooks and contains relevant information about the economy and the firm's industry. The asset value is an appraisal and has to be understood in the context of the business and industry risk; hence *the risk of the asset value* is one of the important elements. It is measured by asset volatility and is closely related to the firm size and industry. Lastly there is a measure of the magnitude of the firm's liabilities called *leverage*. The probability of default increases as the book value of debt approaches the market value of the firm's assets, until the firm defaults when the asset value is insufficient to repay the liabilities (Crosbie & Bohn 2003). The most well known structural model proposed to estimate the default probability is the Merton model (Byström 2005).

3.2 The Merton model

In 1974 Robert C. Merton introduced a market-based model to calculate probability of default. Merton (1974) expanded the Black and Scholes framework from 1973, proposing that option-pricing theory could be used to value corporate liabilities. The firms are assumed to have only zero-coupon debt and the company's equity is characterized as a European call option on its assets with a strike price equal to the face value of debt. Should the assets be of lower value than the liabilities, the call option will not be exercised and the firm will default. Critical assumptions for the model to hold are the market for trading the securities is open most of the time and the value of the firm, V_A, can be explained by equation (1):

$$dV_A = (\alpha V_A - C)dt + \sigma V dz \qquad (1)$$

Where α is the expected rate of return on the firm per unit time and C is the total payouts per unit time to shareholders and liabilities-holders. **σ** is the volatility of the return on the firm per unit time and **dz** is a standard Gauss-Wiener process.

The value of the equity is given by equation (2):

$$V_E = V_A \emptyset(x_1) - Be^{-r\tau}\emptyset(x_2) \tag{2}$$

where V_E is the market value of equity, V_A is the market value of the firm's assets, B is the total amount of the firm's debt, r is the risk free interest rate, τ is time to maturity of the firm's debt and $\emptyset$ is the standard normal distribution function. x_1 and x_2 are given by equations (3) and (4).

$$x_1 = \left\{log[V_A/B] + \left(r + \frac{1}{2}\sigma_A^2\right)\tau\right\}/\sigma_A\sqrt{\tau} \tag{3}$$

$$x_2 = x_1 - \sigma_A\sqrt{\tau} \tag{4}$$

where σ_A is the asset volatility.

Equity and asset volatility are related by expression (5) (Byström 2003).

$$\sigma_E = \frac{V_A}{V_E}\emptyset(x_1)\sigma_A \tag{5}$$

By solving the non-linear system of equations containing (1) and (5) gives expression (6) which is also known as the distance to default.

$$DD_{Merton} = \left\{log[V_A/B] + \left(r - \frac{1}{2}\sigma_A^2\right)\tau\right\}/\sigma_A\sqrt{\tau} \tag{6}$$

The distance to default measures how many standard deviations away from default the firm is. The probability of default is hence the probability that the firm value will diminish more than the number of standard deviations implied by the distance to default. A large distance to default is, by definition, implying a small probability of default.

There have been many modifications of the Merton model over the years; one simplification is proposed by Hans Byström (2003). He simplifies the expression for the distance to default based on three assumptions. $\emptyset(x_1)$ is assumed to be close to one and the drift term $\left(r - \frac{1}{2}\sigma^2\right)\tau$ is 'small' compared to the first term, $log[V/B]$, and is often assumed to be zero. The final assumption is that the default barrier is equal to the book value of debt. The leverage ratio, B/V, is hence calculated using book value of debt. By assuming that the drift term is equal to zero and making the common assumption that the time to maturity of debt is one year the modified expression for distance to default is given in equation (7).

$$DD = log[V_A/B]/\sigma_A$$

By using equation (5) and the assumption of $\emptyset(x_1)$ being close to one we end up with:

$$DD = \frac{log[V_A/B]}{\sigma_E V_E/V_A} \quad (8)$$

Byström defines the leverage ratio as $L=B/V_A$ and gets to the simplified expression for distance to default:

$$DD_{Byström} = \frac{\log 1/L}{\sigma_E(1-L)} = \frac{logL}{(L-1)}\frac{1}{\sigma_E} \quad (9)$$

In equation (9) we can see that factors driving the distance to default, and indirectly probability of default, are the leverage ratio and the equity volatility. These variables will be used in our regression as well as the stock price. The stock prices give an indication about the market's beliefs in the future of the firm. According to Byström (2005) there is some evidence of firm-specific information being implanted into stock prices before it affects the CDS spreads.

3.3 Credit Default Swap (CDS)

A credit default swap is a kind of credit derivative contract designed to transfer the credit exposure from one party to another. It works like an insurance contract against a default, or another credit event. The CDS purchaser pays a premium to the seller until the expiration of the contract; this is compensating the seller for bearing the default risk. The amount of payments made per year by the buyer is known as the credit default swap spread. In case a credit event occurs before the contract matures, the seller is obliged to compensate the CDS buyer and take possession of the underlying entity (Yu 2006).

When the CDSs were introduced by the mid 1990s the market was craving for a more flexible risk management tool. The use of credit default swaps to trade and hedge credit risk quickly became very popular. By buying a credit default swap the credit risk of the reference entity is replaced by the default risk of the CDS seller. This usually reduces the credit risk exposure, which means the purchaser can free regulatory capital that can be used for more productive investments. The main difference between a CDS contract and a regular insurance is that the buyer of the credit derivative doesn't have to own the reference entity. This allows for speculation on the credit worthiness of the underlying entity where investors can take long or short positions in the CDS according to their opinion on the default risk relative to what is implied by the credit default swap spreads (Weistroffer 2009).

When a protection buyer and seller enter the CDS contract they have to agree on an insurance premium. The spread is calculated to cover the expected loss of the underlying entity. The probability of default and the recovery rate, i.e. the percentage of the face value of debt that can be recovered in event of default, are the main parameters that determine the expected loss and therefore also the CDS spread. The premium is hence a direct measure of a firm's credit risk, determined by the market (Ibid.).

4. Data and descriptive statistics

Data used in our paper work was obtained from Datastream Thomson Reuters, we are hence using secondary data. You should always be critical to the validity, but we consider the database to be reliable. The variables included in the model are collected for a sample of 16 companies that are part of the Swedish OMX equity index for a period of 5 years; June 2008 to March 2013 (see Table 1 for descriptive statistics).

Table 1: Descriptive statistics

Descriptive statistics for the dependent variable CDS (change in %) and the independent regressors leverage ratio, stock price (change in %) and stock price volatility (change in %). Monthly data is used.

	CDS	Leverage ratio	Stock return	Volatility
Mean	0.0143	0.5721	0.0103	0.3922
Median	-0.0089	0.5320	0.0148	0.3459
Std. Dev.	0.1767	0.2765	0.1042	0.2433
Skewness	3.1305	0.2558	-0.0015	2.2991
Kurtosis	23.9194	1.9240	6.2372	19.1317
5th Percentile	-0.1866	0.1677	-0.1671	0.1002
95th Percentile	0.3011	0.9361	0.1633	0.8274
Min	-0.3881	0.1096	-0.4185	0.0365
Max	1.7005	1.2469	0.5894	3.0691
Jarque-Bera	18754.94	55.84	412.18	11067.41
Correlation with CDS	1	-0.0004	-0.3805	0.1565

The credit default swap spreads for firm's debts with five years to maturity and stock prices are selected monthly for each entity. The change (in %) in the variables will later on be used in the regression. The reason for choosing credit default swaps with five-year maturity is because it is the most liquid market (Ericsson, Jacobs & Oviedo 2004). Even so, the CDSs are not continuously traded on a daily basis and therefore we use monthly observations instead of daily.

The monthly changes in % for the CDS spread and stock price is computed by subtracting the value from previous month from the value from the present month and then dividing it by the value from previous month.

$$\Delta x_i = \frac{x_t - x_{t-1}}{x_{t-1}}$$

A positive (negative) change in the stock price is expected to decrease (increase) the CDS spread. It seems reasonable to believe that the market's reactions and beliefs in the future of the company would affect both the stock market and the CDS market in a similar way.

The monthly equity volatility was estimated using observations of daily stock prices:

$$\sigma_{monthly} = \sqrt{\frac{\sum_t^T (x_t - \bar{x})}{(T-1)}}$$

where x_t corresponds to each value within the month, $\bar{x}$ is the mean of all values within the month and T is the number of trading days in that month. The equity volatility is expected to be positively correlated with the CDS spread. A higher volatility means more uncertainty, a smaller distance to default and a higher probability of default.

The leverage ratio is collected yearly for the companies and for every year the value from the preceding year is used. The leverage ratio was available in Datastream and calculated as:

$$leverageratio = \frac{Total\ debt}{Total\ capital}$$

where total debt includes all long-term and short-term obligations and total capital includes the company's debt and shareholders' equity. The leverage ratio gives an idea about how a firm finances its operations. A high leverage ratio may indicate financial weakness where the cost of this large portion of debt can increase the probability of default. The leverage ratio is hence expected to be positively correlated with the CDS spread.

Our final panel data is comprised of 944 observations for each variable under analysis across 59 months for 16 companies that belong to the Swedish market.

Figure A1 shows the average equity volatility for the companies. Electrolux, SKF and Volvo have the highest equity volatility during this time period. The lowest monthly volatility is associated with Ericsson, TeliaSonera and Swedish Match.

The leverage ratio varies a lot between companies (see figure A2). The four banks included in our sample have all high leverage ratios, which is natural for financial institutions. Swedish Match though has an equally high leverage ratio.

5. Methodology

5.1 Panel data analysis

Data can be analyzed in different ways, commonly by using cross-sectional data, time series or panel data. Cross-sectional data refers to observations from different subjects at the same point of time while a time series contains observations from one subject over time. Panel data combines these, time and space dimensions and is beneficial when it comes to studying the effect of changes. You are able to get more informative data and efficient econometric estimations (Gujarati & Porter 2009, pp.591-592). Using panel data is advantageous since you can get a larger sample, greater variation in the independent variables as well as pay regard to heterogeneity (Murray 2006, p.679-680).

The program used to carry all the analysis is R 3.0.0 for 32 bit system with cross check in Eviews 7. A part of the code used in R was made available by Oscar Torres-Reyna (n.d.).

We start our analysis by visually evaluating the homogeneity of the sampled CDS. There might be an identification issue in the case of non-exogenous independent variables and heterogeneous estimates (Arellano 2009, p.4). We would like to be aware of any possible unobserved factors undertaken by the shocks that might be correlated with our explanatory variables; this is known as heterogeneity bias (Verbeek 2012, p. 412). We have plotted the heterogeneity of CDS across firms and time with a 95% interval around the mean. By comparing the two graphs we can deduct that time effects are more persistent and have higher spikes than the individual firm effects. Our preliminary findings could be a good indicator of the methods to be used further on into the data modeling.

To control for heterogeneity between the companies we use *'the fixed effects model'.* To pay regard to these company specific characteristics one firm will act as the reference company and the other firms will each be assigned a dummy variable. By doing this we allow the intercept to vary from company to company, but not over time. The individual intercepts, α_i, capture all time-invariant differences between the companies. The slope coefficient will still remain the same among the firms. In the same way we add a dummy variable for each month, except for one, to control for time specific variation. What we get then is a *'two-way fixed effects model'* (Gujarati & Porter 2009, p. 594ff.).

There are many advantages that come with using the fixed effects model, but there are also potential problems to alert. If too many dummy variables are used the degrees of freedom diminishes and multicollinearity problems may arise. Identifying the effect of variables that do not vary over time can be problematic since the company specific intercepts absorb all heterogeneity in the variables (Ibid.).

Many macro economic and financial variables tend to grow over time without returning to an expected value or linear trend. Such a time series is then non-stationary and may cause spurious regressions. The properties of the OLS estimator require for the time series to be stationary. A random variable is weakly stationary if its expected value and variance is constant over time and the covariance function does not depend on time (Westerlund 2005, pp. 201-207). We carry on the analysis by inspecting our data for stationarity, first visually by plotting the four variables individually for each of the 16 companies chosen. The data starts from second quarter of 2008, during the explosive spread of the financial crisis. As a consequence it appears to be a period of higher volatility in the beginning of the series for most of the companies that diminish over time. This behavior looks similar with the mean reverting process but they seem to wander around the mean rather than increasing in mean and volatility that would characterize a random walk. Performing an

Augmented Dickey Fuller test confirms we do not have problems with non-stationary variables.

5.2 Models with fixed effects and random effects

We have chosen to test how well the change in the stock price, change in stock price volatility and the leverage ratio affects the change in credit default swap spreads. To be able to include all observations in one regression, but still distinguish between them, we include dummy variables for companies and time and use a *fixed effects model*.

$$rCDS_{it} = \beta_0 + \sum_{j=1}^{N} \alpha_j D_{ij} + \sum_{z=1}^{N} \alpha_z D_{tz} +$$

$$+\beta_s \cdot rStockprice_{it} + \beta_L \cdot Leverage_{it} + \beta_V \cdot rVolatility_{it} + u_{it}$$

$$u_{it} \sim IID(0, \sigma_u^2)$$

where r indicates the change (in %), $D_{ij} = 1$ when $i = j$ and 0 otherwise and $D_{tz} = 1$ when $t = z$ and 0 otherwise.

It could also be that there are other variables that affect CDS spreads, which are not included in the regression. We could account for them by describing a *random effects model* and assuming that α_i are the random factors independently and identically distributed over companies (Verbeek 2012, p. 381). The model becomes:

$$rCDS_{it} = \beta_0 + \beta_s \cdot rStockprice_{it} + \beta_L \cdot Leverage_{it} + \beta_V \cdot rVolatility_{it} + \alpha_i + u_{it}$$

$$u_{it} \sim (0, \sigma_u^2); \;\; \alpha_i \sim IID(0, \sigma_\alpha^2)$$

where $\alpha_i + u_{it}$ represent one error term composed of the individual specific component, α_i, that is constant over time and u_{it} which is assumed not to correlate over time. The correlation of the error terms over time is hence accredited to the individual components (Verbeek 2012, p. 381).

To choose between the two modeling approaches we must look at the perspective of inferences we want to draw about the CDS spreads. The fixed effects model shows us the expected endogenous variable as conditioned by the explanatory variables and the values of α_i (Verbeek 2012, pp. 384-385). The question that arises is whether we want to consider the companies in our sample as unique and not randomly drawn from the entire population of companies that can be found on the CDS market. We do though restrict our research to the Swedish market and companies that serve as entities on the CDS market. Having estimated a random effects regression gives us a more general model for companies randomly selected, from different fields that bear certain characteristics, from the entire population (Ibid.). At this point it might be attractive to choose the random effects model for the purpose of extrapolating our findings to the entire Swedish market population of companies, but this would be somehow naive given the fact that α_i and the vector of variables x_{it} might be correlated leading to inconsistent estimators. The fixed effect approach is also to prefer when the number of entities is quite small and of a specific nature (Ibid.), like the sample we have. We specify different fixed effects models, which we compare with random effects by carrying out the Hausman test. The null is that the errors in the model are not correlated with the regressors against the alternative of using a fixed effects specification for addressing the correlation problem. We are able to reject the null, concluding that using fixed effects will draw better estimates.

We have chosen to estimate four different models to be able to distinguish between the effects of the dummy variables. Model 1 is a simple OLS without any dummy variables. In model 2 and 3 we introduce the fixed effects by using Least Squares Dummy Variables estimators that are sensible to the individual or time specific effects. The fourth model is a two way fixed effects model where both time and company dummies are included.

To estimate a panel data model with the simple OLS we have to impose the usual assumptions in order to obtain unbiasness, consistency and efficiency of the model. Having unobserved heterogeneity we might find more reliable estimates with a fixed effects model that would account for this issue by including individual-specific intercepts (Verbeek 2012, pp.373-374).

In a multiple regression analysis you want to be able to separate the effect of the different variables. To interpret the slope coefficient it has to be under the assumption that everything else remains constant, the ceteris paribus condition. In a regression analysis we look at the correlation between two variables, but it doesn't tell us in what direction they influence each other. Verbeek (2012, p. 60) states that to be able to make a causal interpretation the ceteris paribus condition should include all variables, observed and omitted. Due to the small guidance statistical tests provide in this matter we should be careful assigning a causal interpretation to estimated factors.

The multiple regression analysis is based on six assumptions. The dependent variable can be written as a linear function of an intercept, explanatory variables and an error term. To be able to draw conclusions about the model the error term, u_{it}, has to be normally distributed. Despite the distribution of the random variables the central limit theorem states that as the sample size grows the distribution of the population approaches normal distribution. A rule of thumb is that the sample should consist of more than 30 observations for the normal distribution to be a good approximation of the true distribution (Westerlund 2005, pp. 58-140). Our sample well exceeds this limit value, hence we can assume normal distribution.

The error term has to be homoskedastic, this means to have the same variance for all observations. If they show a systematic behavior over the observations there is a correlation between the size of the independent variables and the scattering of the error terms, this is known as heteroskedasticity. The presence of heteroskedasticity can invalidate significance tests and the normal variance-covariance-matrix cannot be correctly estimated (Westerlund 2005, pp. 173-181). We ran a Breusch-Pagan test and rejected the null of homoskedasticity for different model specifications.

The observations have to be independent and have a zero covariance; otherwise there is an issue with autocorrelation. Working with time series data, where the observations are chronologically ordered over time, it is likely that the error term is correlated with its earlier values. The effects of autocorrelation are similar to those coming from heteroskedasticity (Westerlund 2005, pp. 185-190).

Running the Breusch-Godfrey/Wooldridge test for serial correlation in panel models we conclude that our sample it is subject to serial correlation.

Another concern would be cross-sectional dependence (CD) as argued by Baltagi (2005, p.197), when one tries to model panel data with cross-section over individuals, firms in our case, it is likely to face contemporaneous correlation. For this purpose we run a Breusch-Pagan based on Lagrange multiplier test and a Pesaran CD test. Under different structural forms the model indicates presence of cross-sectional correlation.

To prevent us from running into biased test results we can relax the assumption of independent distributed residuals but which are uncorrelated between clusters (Hoeckle n.d.). As it was shown by Arellano (1987) we use a fully general structure of the standard errors that account for all of our issues; heteroskedasticity, serial- and cross sectional correlation (Croissant & Millo n.d.).

Another assumption is that the error term has to have an expected value of zero. If that is not the case, the OLS estimator is no longer unbiased. This problem can arise from leaving out variables that otherwise would have been significant in the model. Unexpected signs or sizes of the parameters indicate that a relevant variable has been left out (Westerlund 2005, p. 157).

In a multiple regression you should not be able to predict an explanatory variable with a linear combination of the other variables. This phenomenon, called multicollinearity, does not affect the predictive power of the model as a whole, but you cannot draw inference from individual predictors and it is hard to tell which one of them that causes the variation in the dependent variable (Westerlund 2005, pp. 159-160).

A goodness-of-fit measure, R^2, shows how well our model explains the variation in Y. One drawback with the R^2-measure is that it can never diminish whenever we add another variable, even though the extended model might be less accurate. The $R^2_{adjusted}$- measure gets around this problem by punishing for the increasing number of variables (Andersson, Jorner & Ågren 2007, p. 94). Since it is not clear how this punishment is performed we will use R^2 as our goodness-of-fit measure. You should though be aware of the fact that an increasing R^2 partly could be the consequence of an increased number of variables in the model. The significance level α is the criterion used for rejecting the null hypothesis; it shows the probability of rejecting a true null. We have chosen a 5% significance level throughout the paper.

6. Result and discussion

Prior to report our results we test for multicollinearity problems by first looking at the correlation between the regressors and then by using the variance inflation factor (VIF).

The low correlation values (table 2) for our independent variables rules out issues with multicollinearity.

Table 2: Correlation matrix

Correlation between independent variables, in this context we observe weak relationship between the three variables and we rule out multicollinearity.

	Leverage	**Stock return**	**Volatility**
Leverage	1	0.0185	0.0616
Stock return	0.0185	1	-0.1340
Volatility	0.0616	-0.1340	1

Being guided by the rule of thumb that we might have a collinearity problem in case that VIF is greater than 10 (Verbeek 2012, p.45), we acknowledge that the result of VIF (see table 3) confirms the absence of a perfect linear relationship in the regressors and we can interpret our results.

Table 3: Variance Inflation factor of independent regressors

VIF indicates how much the presence of collinearity would increase the variance of the estimated parameters from a regression. Generalized VIF is calculated when, in the linear model, the terms have more than one degree of freedom. In this case for the two ways fixed effects we have the factors, firms and time, and is interpreted as the inflation is size of the ellipse for the parameters of the variables in comparison with the case when it would be obtained for orthogonal vectors. We consider a value greater than 10 problematic.

	GVIF	**d.f.**	$\mathbf{GVIF^{1/(2\times d.f.)}}$
Leverage	33.6491	1	5.8008
Stock	2.4893	1	1.5778
Volatility	2.2488	1	1.4996

Our results (see table 2) show that the change in stock price is significant in model 1 and 3 (for the second and third model it is significant on the 10%-level). The coefficient is consistently negative which means that an increase in the stock return has a narrowing effect on the credit default swap spread. This is in accordance with theory where we expected a negative relationship between the change in stock price and change in CDS premium. It is also in line with the results Byström (2005) reached in the study of the European iTraxx index. We find it rational to suppose that the reflections of the market's beliefs in the future of the company would look the same for the stock market and the CDS market. An increasing stock price and a smaller CDS premium both indicate positive views on the future and a lower probability of default.

Table 2: Regression results

We start with a simple OLS that doesn't take the heterogeneity in cross section or over time into consideration. In the second model we control for differences in time and the estimated parameters indicate how much CDS changes between countries when variables increase with one unit. The third model is specified to account for heterogeneity across firms. Estimates show how much CDS changes over time, controlling for differences in companies, when the variables increase with one unit for leverage, volatility and stock return. The 4th model represents a two ways fixed effect estimated as a LSDV (least squares dummy variables) and controls for both time and firms effects, being the model with the highest R^2.

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Variables	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Intercept	-0.0098 (0.0136)	0.472	0.0797 (0.0576)	0.167	0.0812* (0.0430)	0.059	0.1219* (0.0671)	0.070
rStock price	-0.6211*** (0.0933)	0.000	-0.1441* (0.0856)	0.093	-0.5898*** (0.0896)	0.001	-0.1404* (0.0855)	0.100
rVolatility	0.0781*** (0.0781)	0.008	0.0029 (0.0198)	0.883	0.1226** (0.0476)	0.010	0.0128 (0.0286)	0.656
Leverage ratio	-0.0002 (0.0182)	0.993	0.0090 (0.0148)	0.543	-0.3258*** (0.1023)	0.002	-0.1265 (0.0954)	0.185
Company dummies					x		x	
Time dummies			x				x	
R^2	0.16		0.46		0.17		0.47	

Standard errors within parenthesis
* Significance level 10% ; ** Significance level 5%; *** Significance level 1%

In model 1, additionally to stock return, volatility was also significant with a positive slope coefficient. This result is in accordance with the Merton model where a higher leverage ratio gives a smaller distance to default, which in turn indicates a higher probability of default. In many of the previous studies this positive correlation was also detected. The stock volatility implies uncertainty and that seems like a valid reason to increase the CDS premium. Leverage ratio is not significant in this first model. The R^2 is very low (0.16), which indicates there are more things that explain the credit default swap spread than the included variables.

In model 2 we expanded the model by including dummy variables for time. Many of them are significant and the R^2 measure rose to 0.46 showing there are time specific differences that explain a fair part of the change in the CDS spread. The time dummies control for time specific factors that affect all firms during a certain month, such as the trade cycle. Since our sample includes observations from the recession as well as the time of recovery of the economy it appears reasonable to get a significant contribution from the dummies. Other than the dummy variables there are no variables that are significant on the 5%-level. The stock return is significant on a 10 % level with a negative coefficient. This indicates that CDS spread changes negatively by 0.14% from a company to the other controlling by differences in time, when stock return increases by 1%. Volatility has a positive slope coefficient but is far from significant in this model. It might be that the time dummies absorb the effect of the stock price volatility. Since the volatility was higher for all firms during the financial crisis, the variable is hence time dependent. Leverage ratio is not significant in this model either.

In model 3 we exchange the time dummies for company dummies to control for firm specific factors that do not vary over time. Most of the firm dummies are significant and so are the three regressors. This allows us to say that CDS decreases by 0.58% over time, controlling by differences in firms, when stock return increases by one percentage. In the same way controlling by differences in companies, CDS increases with approximate 0.12% when volatility increases by one unit. Those variables take on the expected signs, but the leverage ratio has a negative slope coefficient, which is the contrary to what is expected according to theory. This is also the only model where leverage ratio is significant at all. There might be an issue with this variable stemming from the great differences in leverage ratio between financial firms and non-financial firms. The company dummies help to account for the differences between the firms, but the unexpected sign might be due to the fact that the financial firms have a high leverage ratio but still are stable companies. The R^2 is only 0.17 for this third model, the firm specific factors do not seem to explain as much of the change in the CDS spread as the time specific ones did.

In models 2 and 3 the intercept represents the estimated parameter of the excluded group from the regression, for companies and date groups respectively and we can test overall differences among the firms and different periods that the OMX companies went through. For the third model this structural form allows us to compare different companies with the reference point, which in our case is Assa Abloy. Therefore we take the intercept as being its estimate coefficient and we compare every company to it. However in the case of model 3 the intercept is not significant. Looking at the dummies we observe that there are around eight companies, mostly financial firms, which differ significantly from Assa Abloy. This is consistent with the leverage ratios of the companies taken into consideration. Our regression is able to show significant difference between the benchmark and the highly leveraged companies like Handelsbanken, Nordea and SEB.

In the fourth model we include all variables and get an R^2 of 0.47, which is very close to the goodness-of-fit measure for model 2 (0.46). There are still other variables that explain the CDS spread that are not included in the model. In this fourth model the majority of the time dummies are significant, but among the firm dummies only one is significant. Neither of the explanatory variables are significant, but just as in model 2 the stock return is significant at the 10% level with the negative slope coefficient as suggested by theory. Volatility is once again positively correlated with the CDS spread, but not significant. It seems to be that in the models where we have included dummy variables for time, volatility is not significant. The significance for the change in the stock price is also lowered in these models indicating that the time dummies absorb some of the explanatory power from the variable. The leverage ratio was not significant here either. Since the data for leverage ratio only is provided yearly there are only five different values for each company and it might therefore not be the best specification of the variable because of the infrequent updating. On the other hand, the companies' financing methods rarely change quickly.

To determine which of these four models is the best one we perform a set of F-tests. We conclude that model 2 is the best model of the four we estimated. The tests can be found in table 5 on the following page.

Table 5: F-test for comparing nested models

We use the F-test to compare the four nested models we have by looking at their residual sum of squares. We investigate whether the computed RSS will change significantly by adding additional terms. Model 2 turns out to be the best one.

The F-statistic is computed like follows:

$$F = \frac{(R_1^2 - R_0^2)/J}{(1 - R_1^2)/(N-K)} \text{(Verbeek 2012, p. 67)}$$

$$R_i^2 - Rsquared\ in\ the\ nested\ models, with\ and\ without\ additional\ variables$$
$$J - number\ of additional\ variables, and\ N - K\ degrees\ of\ freedom$$

Models	1 vs. 2	1 vs. 3	3 vs. 4	2 vs. 4
F-test	8.6854	1.2775	8.2755	0.5387
p-value	0.000	0.2093	0.000	0.9196

Model 2 turns out to be the best model we have estimated. We can conclude then that no explanatory variables turned out to be significant according to the significance level we chose and time specific factors play a great role in determining the change of the CDS spread. This makes sense considering the uncertainty and cautiousness associated with recessions. Where we are in the business cycle should affect the premium demanded by the CDS seller to take on the risk of a credit event occurring. The stock return and the CDS spread are both indicators of the beliefs of the market, a negative correlation between them was to expect.

In the second model we used the individual time effects to account for specific influences across the time periods included in the panel data. The intercept represents the estimate of the first period from our sample which was excluded from the dummies and represents the baseline to which we rapport the others. The coefficients of the rest of the months are compounded as differences from the intercept of the regression. As we observed through the carried test before, in our modeling strategy the time-specific effects are quite important and statistically more significant than individual effects. It can be seen that the last quarter of 2008 accounts positively for the percentage change in CDS spread while the ongoing period has a negative influence towards the change. An interesting analysis might arise if we consider a business cycle pattern that the CDS spread follows. There are times with economic growth and crisis that affect all companies, more or less. From the end of 2008 up until the first quarter of 2010 almost all months show significance for the CDS spread differences, after that it gets a bit more mixed up with non-significance. The recent financial crisis seems to have had an impact on the credit default swap premiums. In table A1 a full version of the regression results can be found, with dummy variables included.

The Merton model is based on a number of assumptions; the firms only have zero-coupon debt and the equity is viewed as a European call option on the assets of the firms. The simplified version we use has an additional three postulations. This might not mirror reality very well, but the Merton model is well used and we wanted to try the performance of a streamlined version. Previous researches have multiple times shown that simplified models perform as well as the original model, and sometimes even better. If we have excluded essential variables from the model the error term no longer has an expected value of zero and the results are not valid. Something else that could be an issue is reversed causality, we only look at correlation, not in which direction the variables affect each other. The model is though based on economic theory.

Maybe we could have gotten better results by excluding the financial firms from our sample because of their special characteristics. That would be a proposal for future studies on the subject. We already have a small sample of companies in our study though, restrained by the lack of Swedish companies represented on the CDS market. Having a larger sample might as well have improved our analysis. The minor sample also means the results cannot be generalized for all companies belonging to the Stockholm OMX equity index.

7. Conclusion

The purpose of this paper was to examine how well the Merton-implied variables stock price, stock price volatility and leverage ratio affect the CDS spread. A panel data study has been conducted with a streamlined Merton model as theoretical framework. We have reached the conclusion that the structural model alone cannot explain the change in credit default swap spreads. The stock return gave a significant negative impact on the change of the premium (on the 10% level for two models). The change in volatility turned out to be significant with a positive coefficient in the models where time dummies were not included. Both of these variables have expected signs according to theory. Leverage ratio was only significant in the model with company dummies, it took on a negative value which was not in accordance with theory. The most determinant of the spread was the time specific variation.

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Appendix

Figure A1: Average monthly equity volatility

Monthly equity volatility calculated as an average for the period June 2008 - April 2013. The monthly equity volatility is calculated from daily stock prices:

$$\sigma_{monthly} = \sqrt{\frac{\sum_t^T (x_t - \bar{x})}{(T-1)}}$$

where x_t corresponds to each value within the month, $\bar{x}$ is the mean of all values within the month and T is the number of trading days in that month. All 16 companies from our sample are represented.

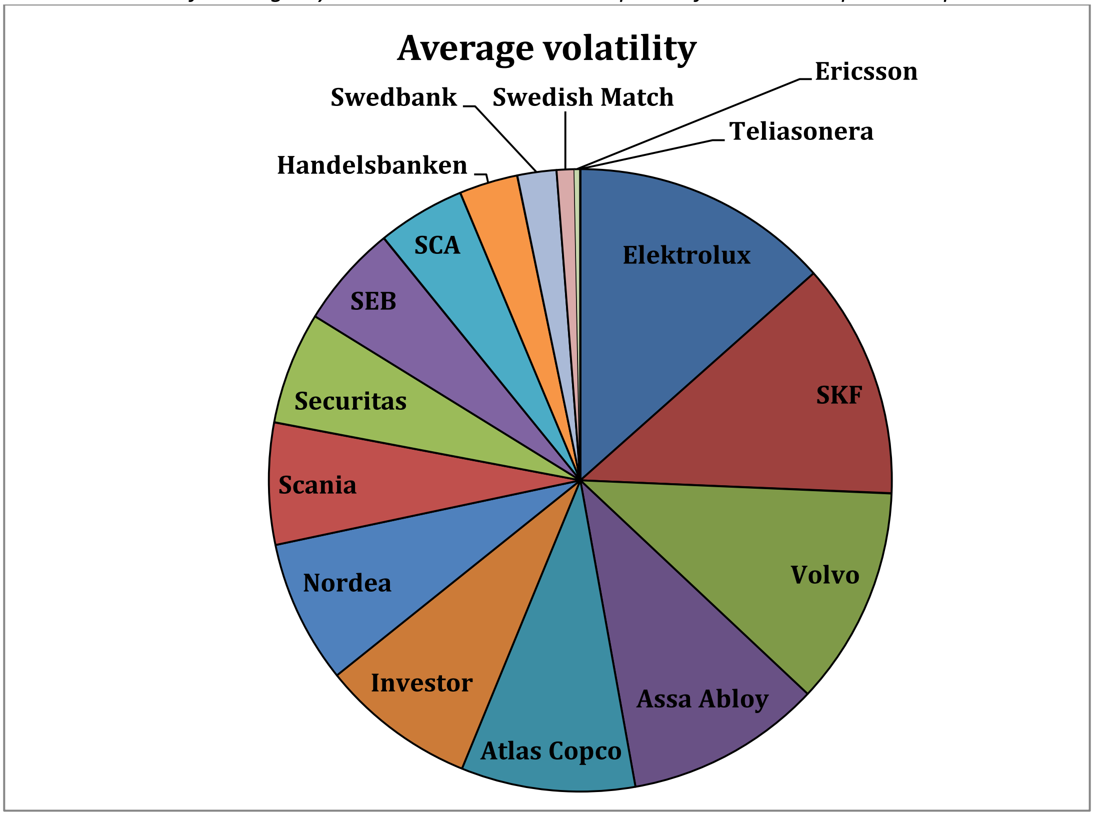

Figure A2: Average leverage ratio for companies included in the sample

The leverage ratio is collected yearly and the value from the preceding year is used. The leverage ratio is calculated as total debt over total capital; where total debt includes long-term and short-term obligations and total capital consists of company's debt and shareholder's equity.

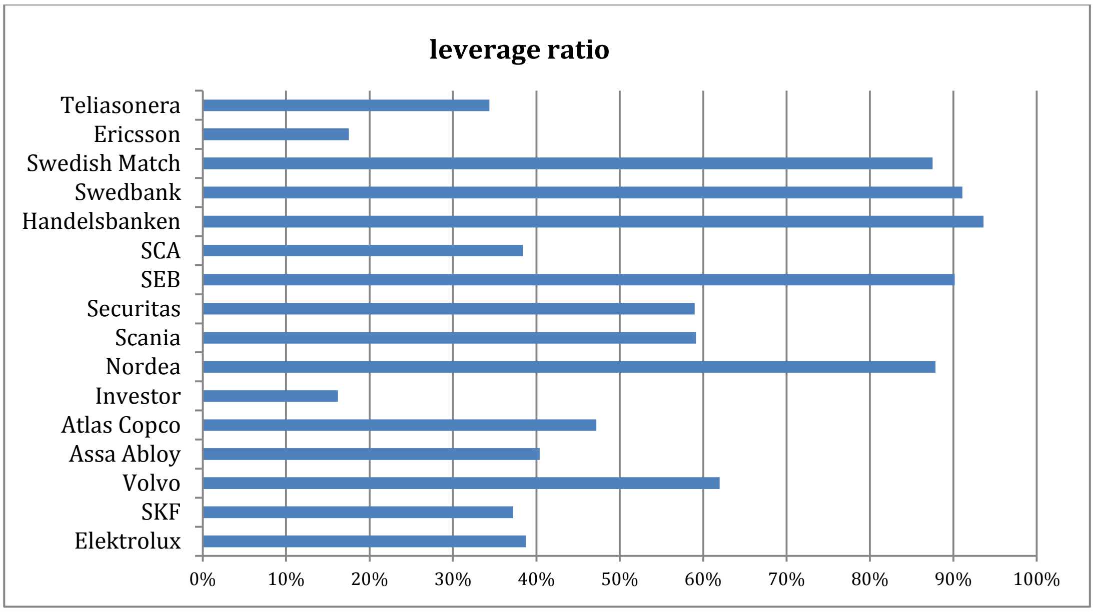

Table A1: Regression result, Arellano standard errors

We start with a simple OLS that doesn't take the heterogeneity in cross section or over time into consideration. In the second model we control for differences in time and the estimated parameters indicate how much CDS changes between countries when variables increase with one unit. The third model is specified to account for heterogeneity across firms. Estimates show how much CDS changes over time, controlling for differences in companies, when the variables increase with one unit for leverage, volatility and stock return. The 4th model represents a two ways fixed effect estimated as a LSDV (least squares dummy variables) and controls for both time and firms effects, being the model with the highest R^2.

	Model 1				Model 2				Model 3				Model 4			
	Estimate	Std. error	p-value		Estimate	Std. error	p-value		Estimate	Std. error	p-value		Estimate	Std. error	p-value	
(Intercept)	-0.0098	0.0136	0.4719		0.0797	0.0576	0.1669		0.0812	0.0430	0.0591	.	0.1219	0.0671	0.0696	.
Leverage	-0.0002	0.0182	0.9928		0.0090	0.0148	0.5431		-0.3258	0.1023	0.0015	**	-0.1265	0.0954	0.1853	
rStock	-0.6211	0.0933	0.0000	***	-0.1441	0.0856	0.0925	.	-0.5898	0.0896	0.0000	***	-0.1404	0.0855	0.1006	
rVolatility	0.0781	0.0295	0.0082	**	0.0029	0.0198	0.8832		0.1226	0.0476	0.0102	*	0.0128	0.0286	0.6558	
Atlas Copco									0.0351	0.0321	0.2740		0.0089	0.0295	0.7623	
Electrolux									-0.0139	0.0298	0.6408		-0.0074	0.0266	0.7798	
Ericsson									-0.0447	0.0350	0.2020		-0.0268	0.0299	0.3701	
Handels-banken									0.1743	0.0712	0.0145	*	0.0806	0.0670	0.2295	
Investor									-0.0684	0.0341	0.0453	*	-0.0298	0.0283	0.2920	
Nordea									0.1968	0.0658	0.0028	**	0.0750	0.0626	0.2306	
SCA									0.0269	0.0303	0.3747		0.0084	0.0285	0.7693	
Scania									0.0885	0.0467	0.0587	.	0.0441	0.0445	0.3225	
SEB									0.2134	0.0686	0.0019	**	0.0799	0.0652	0.2213	
Securitas									0.1064	0.0402	0.0083	**	0.0388	0.0397	0.3289	
SKF									-0.0057	0.0321	0.8589		-0.0009	0.0284	0.9761	
Swedbank									0.1760	0.0664	0.0081	**	0.0608	0.0653	0.3527	
Swedish Match									0.2080	0.0768	0.0069	**	0.0798	0.0741	0.2821	
Teliasonera									0.0176	0.0296	0.5529		-0.0083	0.0285	0.7718	
Volvo									0.1290	0.0541	0.0173	*	0.0689	0.0514	0.1799	
Jul-08					0.1275	0.0737	0.0839	.					0.1286	0.0736	0.0810	.
Aug-08					-0.0900	0.0606	0.1381						-0.0885	0.0612	0.1488	
Sep-08					0.1700	0.0910	0.0619	.					0.1706	0.0920	0.0641	.
Oct-08					0.3320	0.1542	0.0316	*					0.3306	0.1537	0.0317	*
Nov-08					0.0942	0.1063	0.3754						0.0944	0.1073	0.3790	
Dec-08					0.1345	0.0788	0.0882	.					0.1357	0.0791	0.0865	.
Jan-09					-0.2457	0.0570	0.0000	***					-0.2419	0.0571	0.0000	***
Feb-09					-0.0969	0.0627	0.1227						-0.0931	0.0638	0.1445	
Mar-09					0.0417	0.0718	0.5613						0.0459	0.0725	0.5274	
Apr-09					-0.2106	0.0715	0.0033	**					-0.2074	0.0724	0.0042	**
May-09					-0.2803	0.0688	0.0000	***					-0.2755	0.0684	0.0001	***
Jun-09					-0.0785	0.0689	0.2545						-0.0728	0.0696	0.2956	
Jul-09					-0.1364	0.0588	0.0206	*					-0.1342	0.0589	0.0230	*
Aug-09					-0.2514	0.0629	0.0001	***					-0.2476	0.0632	0.0001	***
Sep-09					-0.1771	0.0654	0.0069	**					-0.1718	0.0670	0.0105	*
Oct-09					-0.1343	0.0600	0.0255	*					-0.1291	0.0613	0.0356	*
Nov-09					-0.1270	0.0592	0.0321	*					-0.1221	0.0598	0.0417	*
Dec-09					-0.1139	0.0598	0.0570	.					-0.1077	0.0611	0.0785	.
Jan-10					-0.1638	0.0587	0.0054	**					-0.1610	0.0592	0.0066	**
Feb-10					0.0982	0.0623	0.1154						0.1011	0.0626	0.1067	
Mar-10					-0.1514	0.0581	0.0093	**					-0.1488	0.0587	0.0115	*
Apr-10					-0.1151	0.0571	0.0443	*					-0.1133	0.0573	0.0482	*
May-10					0.0189	0.0557	0.7343						0.0205	0.0558	0.7133	
Jun-10					-0.0227	0.0602	0.7065						-0.0208	0.0607	0.7312	
Jul-10					-0.1150	0.0573	0.0451	*					-0.1136	0.0572	0.0476	*
Aug-10					-0.1107	0.0660	0.0936	.					-0.1088	0.0666	0.1029	
Sep-10					-0.0624	0.0596	0.2954						-0.0604	0.0601	0.3151	
Oct-10					-0.1335	0.0585	0.0227	*					-0.1309	0.0590	0.0269	*
Nov-10					-0.1162	0.0600	0.0530	.					-0.1130	0.0609	0.0636	.
Dec-10					-0.0752	0.0586	0.2001						-0.0727	0.0594	0.2215	

Table A1: Regression result, Arellano standard errors (continues)

	Model 1			Model 2				Model 3			Model 4			
	Estimate	**Std. error**	**p-value**	**Estimate**	**Std. error**	**p-value**		**Estimate**	**Std. error**	**p-value**	**Estimate**	**Std. error**	**p-value**	
Jan-11				-0.0931	0.0604	0.1240					-0.0940	0.0614	0.1257	
Feb-11				-0.1382	0.0568	0.0151	*				-0.1385	0.0572	0.0156	*
Mar-11				-0.0727	0.0552	0.1881					-0.0736	0.0552	0.1827	
Apr-11				-0.0802	0.0575	0.1637					-0.0814	0.0574	0.1565	
May-11				-0.0948	0.0569	0.0962	.				-0.0949	0.0575	0.0992	.
Jun-11				-0.0388	0.0548	0.4789					-0.0410	0.0546	0.4525	
Jul-11				0.0072	0.0606	0.9059					0.0043	0.0604	0.9431	
Aug-11				0.1676	0.0640	0.0089	**				0.1650	0.0632	0.0092	**
Sep-11				0.0962	0.0609	0.1148					0.0945	0.0609	0.1213	
Oct-11				-0.0553	0.0593	0.3513					-0.0585	0.0585	0.3177	
Nov-11				-0.0782	0.0557	0.1612					-0.0805	0.0557	0.1485	
Dec-11				-0.0480	0.0613	0.4334					-0.0486	0.0618	0.4314	
Jan-12				-0.1567	0.0620	0.0117	*				-0.1543	0.0624	0.0137	*
Feb-12				-0.1784	0.0669	0.0078	**				-0.1752	0.0686	0.0108	*
Mar-12				-0.1889	0.0571	0.0010	***				-0.1856	0.0578	0.0014	**
Apr-12				0.0068	0.0600	0.9093					0.0101	0.0600	0.8662	
May-12				-0.0080	0.0592	0.8923					-0.0056	0.0584	0.9236	
Jun-12				-0.1104	0.0596	0.0644	.				-0.1073	0.0607	0.0775	.
Jul-12				-0.0797	0.0589	0.1768					-0.0770	0.0587	0.1898	
Aug-12				-0.1713	0.0595	0.0041	**				-0.1681	0.0605	0.0056	**
Sep-12				-0.2050	0.0586	0.0005	***				-0.2017	0.0588	0.0006	***
Oct-12				-0.0736	0.0594	0.2159					-0.0703	0.0600	0.2414	
Nov-12				-0.0611	0.0569	0.2834					-0.0570	0.0577	0.3233	
Dec-12				-0.1453	0.0610	0.0174	*				-0.1411	0.0624	0.0239	*
Jan-13				-0.1095	0.0569	0.0546	.				-0.1060	0.0576	0.0661	.
Feb-13				-0.0536	0.0579	0.3554					-0.0510	0.0580	0.3796	
Mar-13				-0.0983	0.0583	0.0920	.				-0.0945	0.0591	0.1103	
Apr-13				-0.0909	0.0563	0.1069					-0.0894	0.0558	0.1090	
R -squared		0.1562			0.4629				0.1733			0.4679		
F-statistic		59.99			12.46				10.77			10.03		
P-value		0.000			0.000				0.000			0.000		

Standard errors :
'.' Significance level 10% '*' Significance level 5% '**' Significance level 1% '***' Significance level 0.1%