STOCKHOLM SCHOOL OF ECONOMICS

MASTER THESIS IN FINANCE

Macro Economic Factors and Probability of Default

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ABSTRACT

Business cycles can have great impact on the profitability of individual firms. Therefore, they influence the risk profile of a given company or industry. This paper uses a multi factor fixed effect model to analyze the effect of certain macro economic factors on the probability of default on an industrial level. Monthly analysis is carried out using data of EDF (Expected Default Frequency) and other macro economic indicators from April 2000 to September 2005. The study verified the relationship between macroeconomic factors and the probability of default quantitatively.

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1 Introduction

Credit risk measurement and management has become an area of rapid innovation in the recent years. The increase in bankruptcies, the declining and volatile values of collateral, the growth of off-balance-sheet derivatives, all contribute to this increased importance. Moreover, under the proposed Internal Rating-Based (IRB) approach in the New Basel Capital Accord (Basel 2001), the Basel Committee on Banking Supervision allows banks to calculate regulatory capital charges for credit risk based on bank's internal credit risk ratings for their exposures. Therefore, the demand for banks to have accurate credit risk analysis and sensitivity analysis on loan portfolios have become greater now than in the past.

Credit risk is defined as the risk of loss resulting from failure of borrowers to meet their payments obligations. It is the dominant source of risk for commercial banks. There are several concepts that help analyze credit risk, such as Default Probability, Loss Given Default, and Migration Risk. All these concepts are important for evaluating credit risk, but the most critical factor is the Probability of Default, which is the likelihood that a loan will not be repaid and fall into default.

The estimation of Probability of Default is usually obtained through taking into account the credit history of the borrower and the nature of investment. Yet, there is another aspect which needs to be taken into consideration: the status of the general economy. This can intuitively be traced back to the relationship of business cycle and the individual firms within an industry. This relationship can be discovered further in two ways, from the individual firm perspective and also through the analysis of bank's loan portfolios. The business cycle affects firm's performance. Business cycles also have great impact on the credit portfolio of banks, since the loan is made up of different individual loans representing different companies, and it is usually large enough to diversify away the idiosyncratic risk, leaving only the influence of macro factors. Studies have been carried out taking macro factors into consideration when analyzing probability of default, Jonsson et al (1996), Fridson et al (1997), and Wilson (1997) etc.

Given the importance of business cycles on the analysis of probability of default, this paper aims to explore the relationship between several macro economic factors and the probability of default and further verify this relationship quantitatively. This paper will also analyze the sensitivity of each studied industry to the changes of macro factors. The study uses multifactor econometric models. Data of Probability of default on an industry level as well as the chosen economic indicators are from April 2000 to September 2005. The use of EDF from the KMV model, which is calculated based on both firm's individual information as well as the stock price, makes possible for the study to have a reliable proxy for the probability of default. The study is inspired by the presentation on credit risk from the Swedish Central Bank[1].

The study proceeds as follows. Section two is a general discussion about credit risk and a description of four different credit risk measurement models are provided. Section three discusses more in detail the importance of business cycle on firm's risk profile. Section four describes the calculation of EDF and gives more specific details on the KMV model. Section 5 describes the dependent and independent variables chosen for this analysis. It also contains a data description as well as a presentation of the analysis method used for this study. Empirical results for Sweden, as other European countries and the US are displayed and commented in section 6. The study is concluded in section 7.

2 Preliminary Discussion about Credit Risk

2.1 Credit Risk

Credit risk measurement and management has become one of the most important topics in finance today. The increase in bankruptcies, the declining and volatile values of collateral, the growth of off-balance-sheet derivatives, all contribute to this increased importance. Furthermore, under the proposed Internal Rating-Based (IRB) approach in the New Basel Capital Accord (Basel 2001), the Basel Committee on Banking Supervision allows banks to

[1] P. Nimander, M. Omberg and P. Asberg-Sommar, 2006, Kreditrisk, Swedish Central Bank

calculate regulatory capital charges for credit risk based on bank's internal credit risk ratings for their exposures. Therefore, the demand for banks to have accurate credit risk analysis and sensitivity analysis on loan portfolios have become even greater now than in the past.

Credit risk is typically defined as the risk of loss resulting from failure of borrowers to repay their payments. For a bank, this is the risk that a borrower fails to make the contractual payment on a timely basis. Credit risk is one of the dominant sources of risk for commercial banks. Credit risk, or default risk, can be well determined from company's perspective. Default risk is the uncertainty of a firm's ability to service its debts and obligations. Prior to default, there is no way to discriminate between firms that will default and those that will not. At best, we can only make probabilitistic assessments of the likelihood of default. Therefore, the Expected Loss, which is the final result searching by many banks, calculated as the product of Default Probability and the Loss Given Default, can only be estimated depends on Probability of Default. Default is rare. On average, the firm has a probability of default of around 2%[2] in any year. However, there is considerable variation in default probabilities across firms. The loss suffered by a lender or counterparty in the event of default is usually significant. Table 1 describes the basic elements of credit risk.

Standalone Risk	
Default Probability	The probability that the counterparty or borrower will fail to service obligations
Loss Given Default	The extent of the loss incurred if the borrower or counterparty defaults
Migration Risk	The probability and value impact of changes in default probability
Portfolio Risk	
Default Correlation	The degree to which the default risks of the borrowers and counterparties in the portfolio are related
Exposure at Default	The size, or proportion, of the portfolio exposed to the default risk of each counterparty and borrower

Table 1 Basic Elements of Credit Risk

[2] KMV corporation

Each of these items is critical to the management of credit portfolios. None is more important or more difficult to determine, than the default probability.

2.2 Credit Risk Measurement

In order to be able to measure credit risk, one has to choose an appropriate credit risk model. The selection of such model is very important for credit risk management. An inadequate model might contain model errors. Those model errors would introduce uncertainty into the credit risk management process. In the recent years, many new approaches have been developed apart from the traditional approaches such as expert system and rating system. These new approaches use different assumptions and information, therefore are usually classified into four categories[3].

- ✧ Structural model, which is based on Merton's Option Pricing Theory;
- ✧ Rating based model, which is based on ratings and rating migrations;
- ✧ Econometric risk factor model, which analyzes the default rate in a multi-factor econometric model;
- ✧ Actuarial model, which is a probabilistic model assuming only two states for a firm, default and not default. This is similar to the way premiums are set for household insurance.

Structural Models

KMV[4] Corporation relies on Merton's model of a firm's capital structure: a firm defaults when its asset value falls below its liabilities. Hence, a borrower's probability of default depends on the amount by which assets exceed liabilities, and the volatility of those assets. If changes in asset value are normally distributed, the default probability can be expressed as the probability of a standard normal variable falling below some critical value. It can be applied to any public company. KMV computes the actual probability of default, the Expected

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[3] For more detailed analysis and comparison of the models, please consult Koyluoglu and Hickman (1998), Crouhy et al (2000) and Saunders, Credit Risk Measurement.

[4] KMV is a trademark of KMV Corporation. Stephen Kealhofer, John McQuown and Oldrich Vasicek founded KMV Corporation in 1989.

Default Frequency (EDF), for each obligor. The EDF is a function of the firm's capital structure, the volatility of the asset returns and the current asset value. Based on stock market data, the EDF is forward-looking. The EDFs used in this study is based on this method. The method will be analyzed more in detail in the following section.

Rating Based approach

CreditMetrics approach from JP Morgan is based on credit migration analysis, i.e. the probability of moving from one credit quality to another, including default, within a given time horizon. It estimates the loan or loan portfolio by viewing rating upgrades and down grades. CreditMetrics models the full forward distribution of the values of any bond or loan portfolio, e.g. 1 year forward, where the changes in values are related to credit migration only. The model uses two assumptions: first, all firms within the same rating class have the same default rate, and second, the actual default rate is equal to the historical average default rate. The model works closely with the rating system, which is where it departs from KMV. In KMV's framework each issuer is specific, and is characterized by his own asset returns distribution, its own capital structure and its own default probability. Whereas in CreditMetrics, the model assumes that all issuers are credit-homogeneous within the same rating class, with the same transition probabilities and the same default probability. This assumption didn't take into account individuality. The issuers might differ by location, business cycles or even the collateral. The portfolio loss distribution is measured by a Monte Carlo Simulation. However, the model has some problems, e.g. the rating transition used in this model might be correlated over time.

Econometric Risk Factor Model

CreditPortfolioView from McKinsey measures only default risk. It is a discrete time multi-period model, where default probabilities are a function of macro-variables such as unemployment, the level of interest rates, the growth rate in the economy, government expenses, which also drive, to a large extent, credit cycles. More in detail, it posits an empirically estimated relationship which drives each borrower's default rate $p_{i,t}$ according to a normally distributed "index" of macroeconomic factors for that borrower. The macroeconomic index $y_{i,t}$ is expressed as a weighted sum of macroeconomic variables, $x_{k,t}$ each of which is normally distributed and can have lagged dependency.

$$x_{k,t} = a_{k,0} + a_{k,1}x_{k,t-1} + a_{k,2}x_{k,t-2} + ... + \delta_{k,t}$$

$$y_{i,t} = b_{i,o} + b_{i,1}x_{1,t} + b_{i,2}x_{2,t} + ... + \upsilon_{i,t}$$

Where $\delta_{k,t}$ and $\upsilon_{i,t}$ are normally distributed. And then the index is transformed to a default probability by the Logit function:

$$p_{i,t} = \frac{1}{1 + e^{y_{i,t}}}$$

Actuarial Model

Credit Risk+ from Credit Suisse Financial Products (CSFP) only focuses on default, like the CreditPortfolioReview. Different from CreditMetric, this model only focus on measuring expected and unexpected losses. In this model, the firm either defaults with a probability of *P* or it does not default with a probability of 1-*P* without assuming the cause of the default. In this model, default of individual bonds, or loans, follows a Poisson process.

$$p(n) = \frac{\mu^n e^{-\mu}}{n!} \quad , \quad n = 0,1,2...$$

Where,

n = the number of companies who default

μ = average number of defaults per year;

Credit migration risk is not explicitly modeled in this analysis. Instead, Credit Risk+ allows for stochastic default rates which partially account, although not rigorously, for migration risk. The model assumes that for a loan, the probability of default in a given period, e.g.1 month, is the same for any other month. And it also assumes that for a large number of obligors, the probability of default of any particular obligor is small, and the number of defaults that occur in any given period is independent of the number of defaults that occur in any other period.

A basic summary of all four models is shown in Table 2.

	Model	Summary
Structural Model	KMV	The default process is endogenous and relates to the capital structure of the firm. Default occurs when the value of the firm's assets falls below some critical level
Rating Based Model	CreditMetrics	Assumes all the issuers are credit-homogeneous within the same rating class, same transition probability and the same default probability. It is based on the probability of moving from one credit quality to another, including default, within a given time horizon. One of the problems is that the rating transition might be correlated.
Econometric Risk Factor Model	CreditPortfolio View	Measures only default risk, it is a discrete time multi period model while default probability are conditional on macro variables and consider only the portfolio instead of the individual issuer
Actuarial Model	Credit Risk+	Only focuses on default. Default for individual bond or loan is assumed to follow an exogenous Poisson process. It assumes that for a large number of obligors, the probability of default of any particular obligor is small, and the number of defaults that occur in any given period is independent of the number of defaults that occur in any other period. This model is of great help in managing portfolios

Table 2 Summary of the four Credit Risk Models

One of the key differences between the models lies in the modeling of default probability. In KMV, EDF is calculated based on firm's own profile as well as the market information. EDF is directly linked with the stock prices and the volatility of the stock prices of the given firms. Therefore, it has great sensitivity. In CreditMetrics, the probability of default is modeled as a fixed or discrete value based on historical data. In CreditPortfolioView, the probability of default is a function of a set of macro factors and firm's own information. In Credit Risk +, the probability of each loan's defaulting is viewed as a variable and conforming to a Poisson distribution around some mean default rate. This model is more useful for portfolio management, since it doesn't really consider individuality.

EDF from KMV model is directly linked to individual firm's default profile, and it is considered to be more accurate when comparing with the modeling of probability of default from other models. Yet, it doesn't really take macro economic factors into consideration when analyzing the probability of default of a certain firm whereas the firm's risk profile is closely linked with the state of economy. In the next section, I'm going to discuss this relationship between the default probability and macro economic factors

3 Macro Economy and Probability of Default

There are two ways of approaching the effect macro economy has on the probability of default. One is to analyze directly from the relationship between business cycle and individual firms. The other is to analyze through bank losses. Many researchers have already done analysis following the two ways and provided promising evidence.

3.1 Business Cycle and probability of default of the firms

The firm's profitability changes with the business cycle. Apart from the management problems and other firm specific issues that would cause a loss in its profitability, changes in market and economic conditions (such as changes in interest rates, stock market indexes, the exchanges rate, the unemployment rates, and industry specific shocks, etc) may affect the overall profitability of the firm. Ross's (1976) Arbitrage Pricing Theory (APT) reflected this idea by defining a firm's change in value (or return) as a function of changes in the underlying macroeconomic variables (the systemic component) and the firm specific idiosyncratic shocks. In general, in an expansion, demand is high and business is strong: firms have higher probability to profit and therefore fewer defaults will happen. Whereas during a recession, keeping a business profitable is more challenging and it is more likely for a firm to default. Carey (1998) and Frye (2000) find that losses are indeed worse in recession. Therefore, it can be concluded that the firm's performance, which is associated with its risk profile, is directly tied to the business cycle and the whole state of macro economy. Researches were carried out to study the probability of default on the individual firm's level. However, only since recent years have the researches about the probability of default have taken into account the influence of macro economic conditions. Same empirical results have been found. Standard credit risk models by Vasicek (1987, 1991, 2002), following the option-based approach of Merton (1974), allow for business cycle effects generally via one or more unobserved systemic risk factors. Empirical evidence linking credit spreads to the business cycle can be found in, for example, Fama and French (1989), Chen (1991), Jonsson et al (1996), Helwege and Kleiman (1997), Wilson (1997a, b), Carling et al (2002). More recently Koopman and Lucas (2005), Ivan Alves (2005), Pesaran et al (2005) studied the dynamic behavior of default rate and credit spread in relation to business cycle development and verified the co-movement of the two. Empirical evidence shows a strong negative relationship between realized defaults and the economic cycle.

3.2 Analyzing firm's probability of default through bank losses

Many studies have been carried out to analyze the loss distribution of the banks, as well as the quality of banks' portfolio. Almost all the banks and other financial institutions have significantly large portfolios of loans, which are made up of individual firms with different profiles, different locations, etc. Diversity helps to reduce uncertainties. Since the portfolio is usually quite large, the idiosyncratic risk is diversified away, leaving only the risk that cannot be diversified, the systemic risk, which is driven by the health of economy. Macro environment have great impact on the bank loss. Carey (2002), using the data from US banks, suggests that mean losses during a period of distress are 3.5 times larger than during an expansion. He also noted that aggregate default rates can be related to the severity of economic downturns. Bangia et al (2002) find that, over a one-year horizon, the banks' need increases by 25-30% in a recession compared to expansions. C. Duffie and Singleton (2003) provide an overview of the interaction between the business cycle and the quality of banks' asset portfolios. The simple intuition is that, when economic is bad, more firms are likely to default, which will result as losses for banks, and vice versa. Since the loan is made up of different individual loans representing different companies, the relationship between individual firms and the business cycle can easily be backed up. In general the losses of the bank as well as the quality of bank's portfolio reflect how each individual firm is tied to the driving factor, the macro economy.

The general idea of my study is to analyze the actual effect chosen economic indicators have on the probability of default on an industrial level and on a monthly basis. To make the study more continuous, I will describe in Section 4 KMV model as well as the calculation of EDF which I use as a proxy of the probability of default.

4 KMV and EDF

Following Merton (1974)[5], a firm is expected to default when the value of its assets falls below a threshold value which is determined by its callable liabilities. If the value of the firm falls below a certain threshold, the owners will put the firm to the debt-holders. The probability of default is thus a function of the firm's capital structure, the volatility of the asset returns and the current asset value. Once the stochastic process for the asset value has been specified, then the actual probability of default for any time horizon, 1 year, etc can be calculated out.

It can easily be concluded that the default risk of the firm increases as the value of the assets approaches the book value of the liabilities, until finally, when the market value of the assets is insufficient to repay the liabilities, the firm defaults. However, Crosbie and Bohn (2003) from the KMV Corporation found out that generally firms do not default when their asset value reaches the book value of their total liabilities, depending on the different nature of industries as well as the long term nature of some of the liabilities. As a result, default can be defined more accurately as the point when the firm's market net value reaches zero, where $MarketNetValue = [Market\,Value\ of\ \ Assets] - [Default\ Point]$[6]

[5] Applying option pricing theory to the valuation of risky loans and bonds, Merton noted that when a bank makes a loan, its payoff is similar to writing a put option on the assets of the borrowing firm.

[6] Default point is the assets value at which the firm will default. It generally lies somewhere between total liabilities and current or short-term liabilities.

In addition, default is generally considered rare. The typical firm has a default probability of around 2% in a year[7], before default, there's almost no way of separating firms that will default or firms that will not. The best thing that is possible to do is to make a probability assessments of the likelihood of the default based on the "signals" sent out from the studied firms.

Therefore, the estimation of the probability of default has become one of the most important and key element in evaluating the credit risk of a certain firm or industry.

There are three main elements that determine the default probability of a firm:

Asset Value*:* the market value of the firm's assets. This is a measure of the prospect of the company and industry. It is calculated from the present value of the future free cash flows produced by the firm's assets discounted back at the proper discount rate.

Asset Risk*:* the uncertainty or risk of the asset value. The value of the firm's assets is an estimate and is thus uncertain. Asset Risk is measured by asset volatility, which is the standard deviation of the annual percentage change in the asset value. Asset volatility relates to the size and nature of the firm's business and represents the business and industry risk of the firm.

Leverage*:* the firm's contractual liabilities, which include short-term liabilities, long-term liabilities, convertible debt, preferred equity and common equity. The relevant measure of the firm's assets is always their market value. The book value of the liabilities relative to the market value of assets is the pertinent measure of the firm's leverage, since that is the amount the firm must repay.

Another important measure KMV implemented as an intermediary phase before calculating default probability, which is a combination of the three factors above, is the Distance to Default. It combines Asset value, Asset Risk and Leverage into a single measure of default

[7] Moody's KMV official documentation, P5

risk which compares the market net worth of the firm to the size of one standard deviation move in the asset value. This value is calculated using the following equation:

$$[Distance\ to\ Default] = \frac{[Asset\ value] - [Default\ Point]}{[Asset\ value][Asset\ volatility]}$$

From the equation above, the default probability can be computed directly if the probability distribution of the assets is known. Basically, information can be obtained from the traded firm's financial statement, market prices of the firm's debt and equity, and subjective appraisal of the firm's prospects and risk.

KMV Corporation has extended Merton's idea by using a model of default probability known as the Vasicek-Kealhofer (VK) model[8]. KMV relies on the ``Expected Default Frequency", or EDF, for each issuer, rather than on the average historical transition frequencies produced by the rating agencies, for each credit class, as in CreditMetrics model. The EDF, expressed as a percentage on a yearly basis, is the probability of default estimated for the forthcoming year, or years, for single companies or groups of companies with publicly traded equity[9]. The EDF is firm-specific, and can be mapped into any rating system to derive the equivalent rating of the obligor. Since it requires equity prices and certain items from financial statements as inputs, EDF reflects information signals transmitted from equity market, which as a result is more sensitive due to the direct link between EDF and the stock market price.

The derivation of the probabilities of default proceeds in 3 stages which are discussed below

- ✧ Estimation of the market value and volatility of the firm's assets;
- ✧ Calculation of the distance-to-default, which is an index measure of default risk;
- ✧ Scaling of the distance-to-default to actual probabilities of default using a default database.

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[8] This model assumes the firm's equity is a perpetual option with the default point acting as the absorbing barrier for the firm's asset value. When the asset value hits the default point, the firm is assumed to default. When the firm's asset value becomes very large, the convertible securities are assumed to convert and dilute the existing equity. In addition, cash payouts such as dividends are explicitly used in the VK model.

[9] According to the KMV documentation, this model can also be modified for calculating the EDF for firms without publicly traded equity.

4.1 Estimate asset value and the volatility of asset return

The idea of applying option pricing theory to the valuation of risky loans and bonds has been in the literature at least as far back as Merton (1974). Having the similarity in payoff patterns, Merton noted this payoff equivalence: when a bank makes a loan, its payoff is isomorphic to writing a put option on the assets of the borrowing firm. Here in KMV model, using the limited liability feature of equity is the same as call options on the firm's assets with a strike price equal to the book value of the firm's liabilities, which can easily be understand as the shareholders hold a put option on the firm while the debt holders hold a call option.

If the market price of the equity is available, the market value and volatility of assets can be determined directly using an option pricing based approach. One of the hypotheses is that the market value of the firm's assets is log normally distributed. The empirical study done by KMV has further consolidated this hypothesis. It is quite straightforward to estimate firm's assets and its volatility if all the liabilities of the firm are traded. The firm's assets value would be the sum of the market values of the firm's assets, and the volatility of the asset return could be derived from the historical time series of the reconstituted assets value. KMV assumes that the capital structure is only composed of equity, short-term debt, long-term debt and preferred shares. Asset Value and Asset Volatility can be solved from the following two relations:

$$V_E = f(V_A, \sigma_A, K, c, r)$$

$$\sigma_E = g(V_A, \sigma_A, K, c, r)$$

Where

V_E denotes the equity value

σ_E is the equity volatility

K denotes the leverage ratio in the capital structure;

c is the average coupon paid on the long-term debt

r is the risk-free interest rate.

Further more, from the first equation; the following relationship can be backed out:

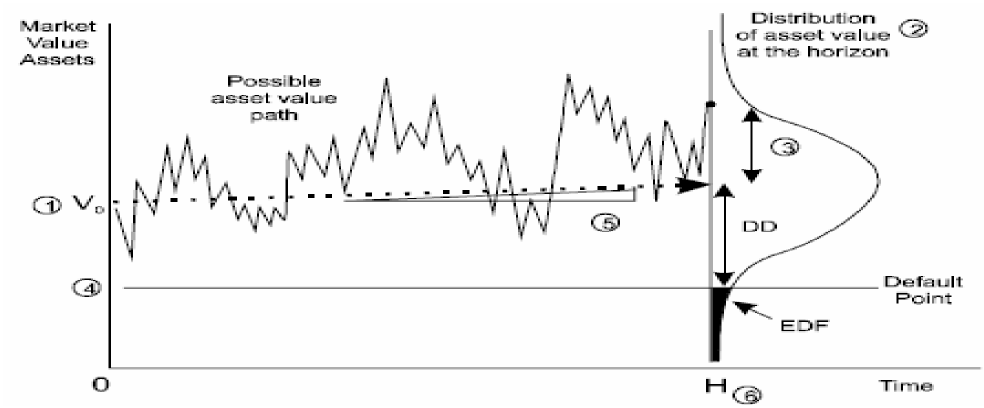
$$V_A = h(V_E, \sigma_A, K, c, r)$$

Therefore, from the three functions above, the asset value of the firm as well as the volatility can be solved.

4.2 Calculate the distance-to-default

Distance to Default can easily be generated by using the same equation as described above:

$$[\textit{Distance to Default}] = \frac{[\textit{Market value of Asset}] - [\textit{Default Point}]}{[\textit{Market value of Asset}][\textit{Asset volatility}]}$$



Where, DD is the distance to default; V is the value of assets

Fig 1 Graphical Description of the Merton Model ***Source: KMV Documentation***

4.3 Scale the default probability

This last step is to scale the Distance to Default calculated from the previous stage into percentage within a certain time horizon. The measures generated from this step are the EDFs of KMV described earlier. Based on historical information on a large sample of firms, a database is created which includes all the firms of the same Distance to Default measure, e.g. 2. Then information on how many of these companies actually defaulted during that time horizon (for example 1 year) can be get from the database. From this, therefore, EDF for that time horizon (i.e. one year) can be calculated out as the quotient of the number of firms defaulted and the total number of firm within that Distance to Default level. Also, EDF can be mapped into ratings. EDF rating from KMV Corporation is shown in table 3.

Quantiles	10	25	50	75	90	Mean
AAA	0.02	0.02	0.02	0.02	0.10	0.04
AA	0.02	0.02	0.02	0.04	0.10	0.06
A	0.02	0.03	0.08	0.13	0.28	0.14
BBB	0.05	0.09	0.15	0.33	0.71	0.30
BB	0.12	0.22	0.62	1.30	2.53	1.09
B	0.44	0.87	2.15	3.80	7.11	3.30
CCC	1.43	2.09	4.07	12.24	18.82	7.21

Table 3 Variation of EDFs within rating classes ***Source: KMV Corporation***

5 Model and Data Description

The general idea of this study is to analyze the relationship between the industrial EDFs and macro factors, in order to see how these factors contribute to explain the probability of default on the industrial level. The study focuses mainly on Sweden, however, the empirical results for other countries such as Norway, Denmark, Finland, Germany, UK and US will be displayed and compared.

I will start with a detailed description of the data. The data in this model are divided into endogenous variable (EDF), and exogenous variables which represent the general state of the economy.

5.1 Data Description

5.1.1 Endogenous Variable – EDF

EDF, as described in the previous section, is calculated using both market information as well as firm individual profile, which makes it more sensitive. In addition, EDFs have been observed to have good early warning properties (Delianedis and Geske 1998). That’s why I choose EDF as a reliable proxy for the Probability of Default.

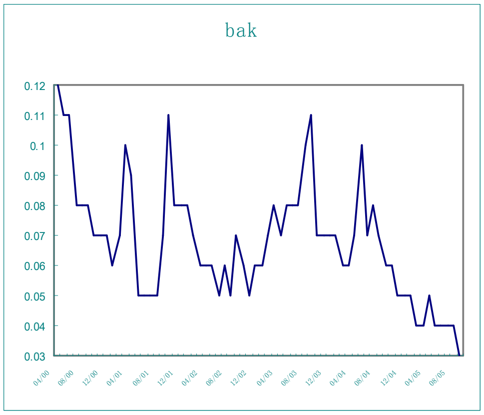
A dataset of monthly EDF, one year time horizon, at the period from April 2000 to September 2005 is obtained from the Swedish Central Bank, which was calculated the same way as described in the previous section. The data set contains EDFs of 7 countries, Sweden, Denmark, Norway, Finland, UK, Germany, US, and finally other industrial countries. Also, since the data is on an industrial level, there are information for 11 industries in Sweden, and similar industries in other countries. The detail of these industries and their abbreviations I will use further in this study are given in the following table (Table 4).

Abbreviation	**Industry**	**Abbreviation**	**Industry**
bak	Bank	trans	Transport
cons	Construction	rest	Real Estate
agri	Agriculture	serv	Service
min	Mining	fin	Financial
manu	Manufacture	oth	Other
sale	Retail/Wholesale		

Table 4 Studied Industries and their abbreviation

There are four different types of EDF within each of the industries: EDF 10 which represents the 10% worst companies in the industry; EDF 25 is the 25% worst; EDF 50 is the industry median; and EDF 75 represents the 25% best companies in the industry. Since the data for the EDF 50 is available for all the industries and all countries, and as this median value is considered to have the most representative power, the study starts with EDF 50. All the EDFs used here are of one year time horizon.

The graphs below are the development of each industry EDF of Sweden. Graphs of Industry EDF of other countries can be found in Appendix.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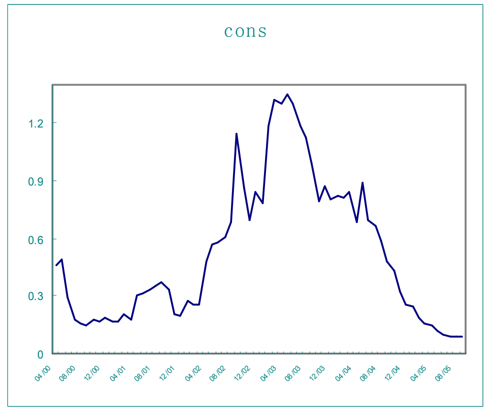
0.04
0.03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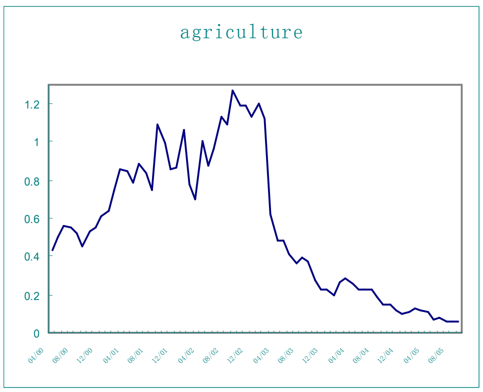
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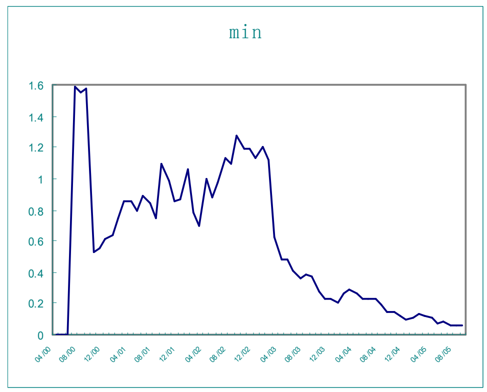
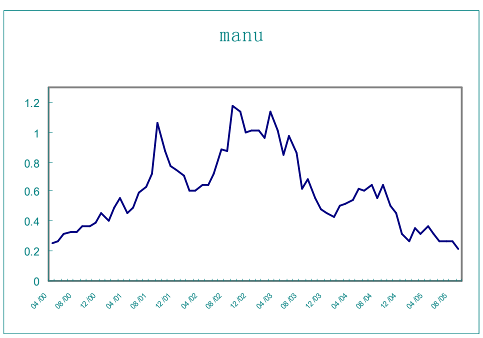

min
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0


manu
1.2
1
0.8
0.6
0.4
0.2
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sale
1.4
1.2
1
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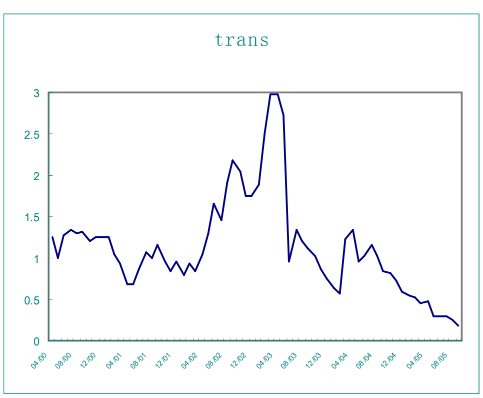
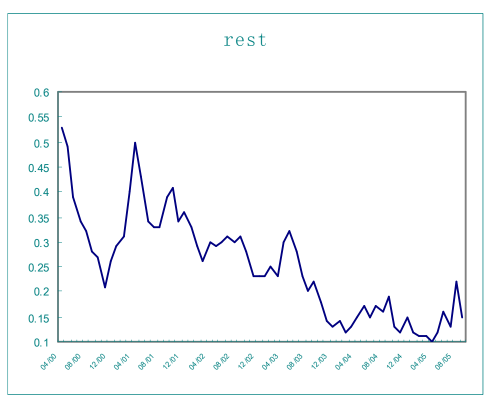
0


trans
3
2.5
2
1.5
1
0.5
0


rest
0.6
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1

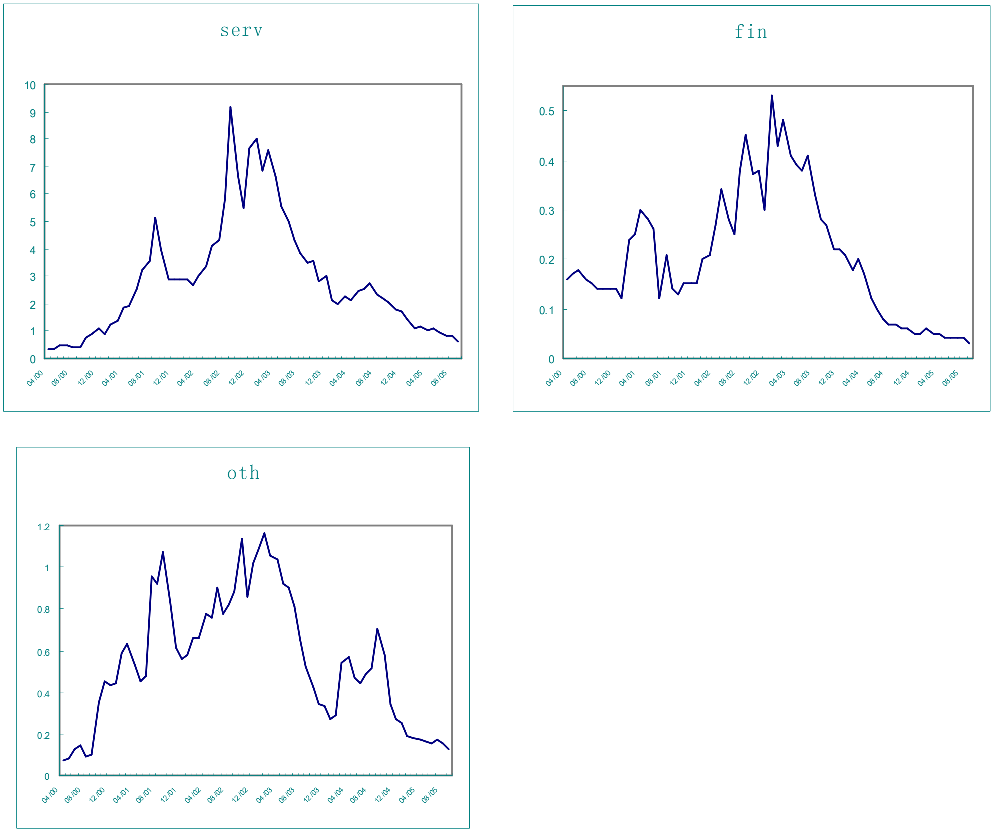


Fig 2 Industry median EDFs (Sweden) in percentage

EDF varies with time and across industries. For most of the studied period, the service sector has the highest EDF, followed by transport, manufacturing and retail/wholesale. The banking sector has the lowest ones, as well as the most stable. Service, manufacture, retail/wholesale and agriculture reached their peak simultaneously at the same time in September 2002, with EDF of 9.18%, 1.18%, 1.37%, and 1.27% respectively. The normalized[10] EDFs are plotted in figure 3.

[10] Divide the EDF by the maximum value of the industry this EDF belongs to, in order to compare the evolution of the EDF in different industries.

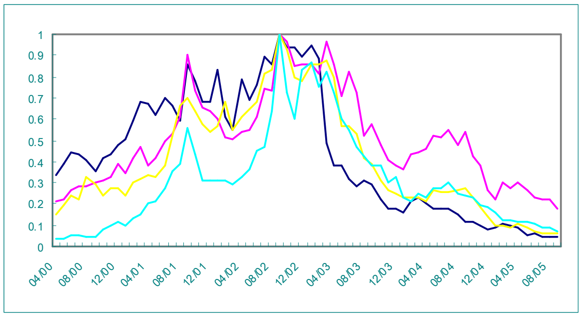


Fig 3 Normalized EDF of 4 industries in Sweden

The similar development trend can easily be observed. However, not only these four industries have been found out to have similar development over time. Plotting the industrial level EDF, all the EDFs in Sweden seem to follow a similar development over time, which I think reflects their reactions to common systemic or general macro economic changes as discussed in section 3 (Macro factors and Default Probability).

The same kind of evolution can be found in the EDF of other countries as well. In general EDFs are driven by general systemic factors, but react with different amplitude.

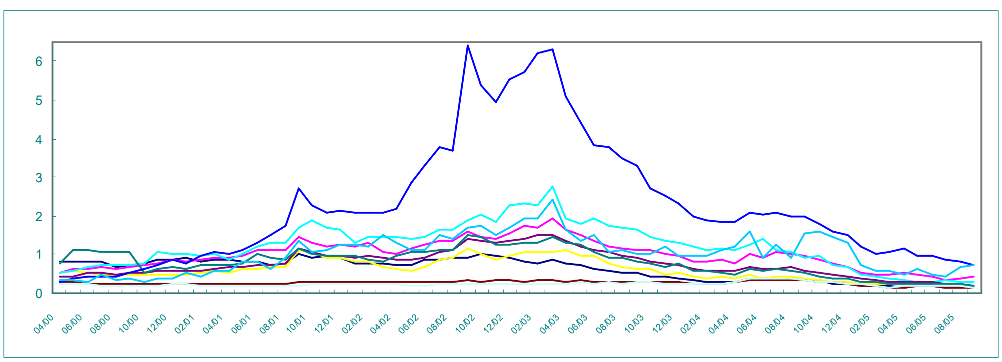


Fig 4 Data from Other industrial countries

---

bak				
0.28	cons			
0.15	0.13	agri		
0.08	0.02	0.82	min	

0.12	0.67	0.68	0.52	manu						
0.1	0.52	0.84	0.68	0.92	sale					
0.26	0.67	0.52	0.46	0.71	0.74	trans				
0.53	-0.1	0.63	0.49	0.2	0.37	0.27	rest			
0.01	0.74	0.6	0.43	0.94	0.88	0.74	0.08	serv		
0.23	0.73	0.62	0.48	0.74	0.79	0.76	0.32	0.79	fin	
0.03	0.57	0.69	0.49	0.92	0.89	0.68	0.23	0.87	0.71	oth

Table 5 Industrial EDF Correlations of Sweden

EDF series are highly correlated across industries, denoting the close interaction of their measure of risk and their possible sensitivity to common systemic or macroeconomic effects and also the impact of one to another: manufacture and service, service and retail/wholesale show strong correlation coefficients, whereas the one with the lowest correlations is the banking sector. EDFs vary across countries, however, within most of the countries, service has the highest EDF, whereas banking and financial sectors have the lowest EDF. Construction in Germany and the Agriculture in UK are the industries with EDFs that vary the most over time, especially during the year 2003 and 2001 respectively. In Finland, all the industries have lower EDFs when comparing with other countries.

5.1.2 Exogenous Variables

The exogenous variables in this study represent the general macro economy state. The variables considered are Industrial Production, CPI, Unemployment Rate (seasonally adjusted), Interest Rate Spread, Share prices and Exchange rate, during the period of April 2000 to September 2005. The evolutions of these variables are plotted in the figures below:

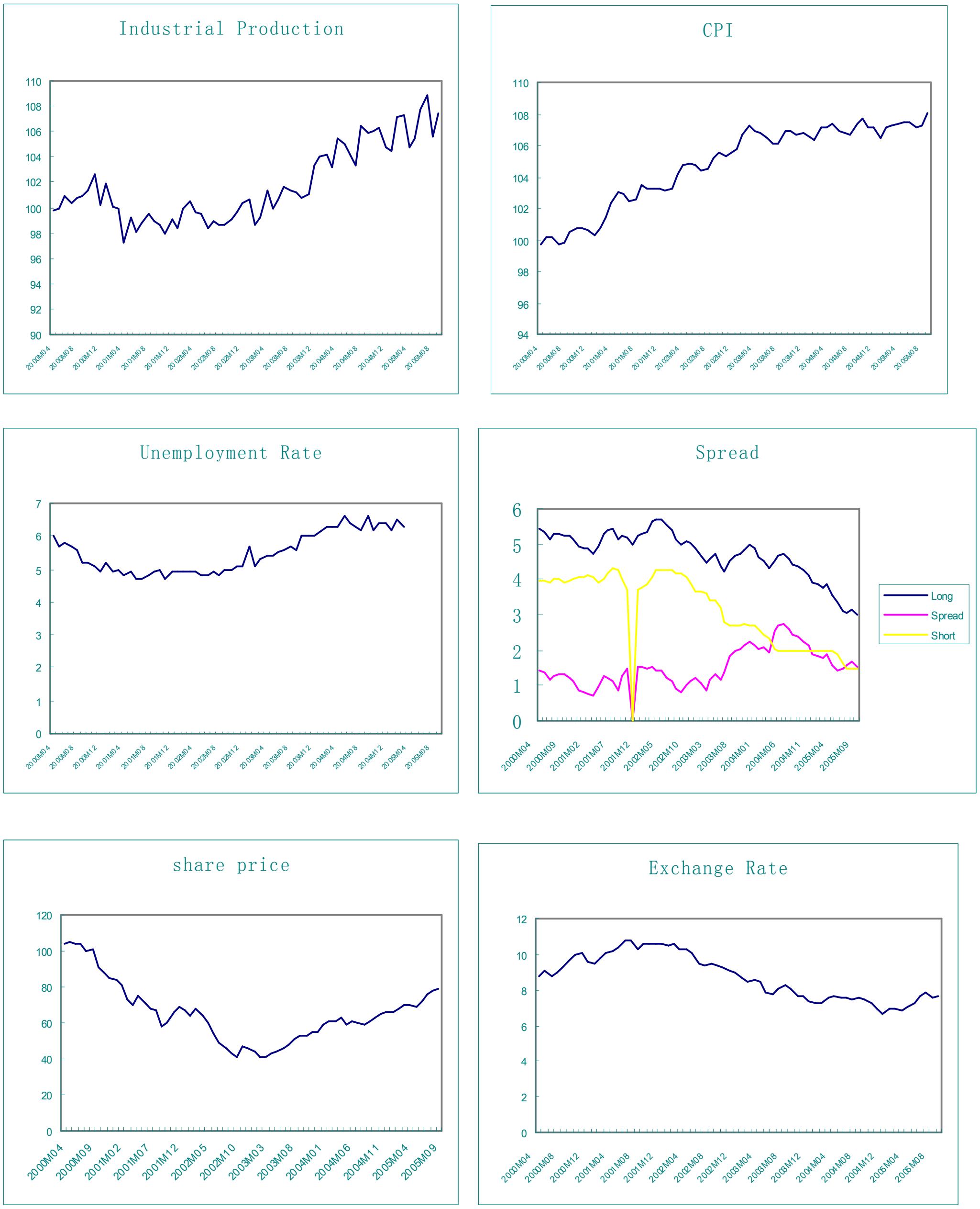


Fig. 5 Macro factors of Sweden

In this study, Industrial Production is chosen instead of GDP in order to make a monthly analysis possible. Industrial Production is considered to be the proxy for the aggregated demand changes. When demand increases, default risks reduce.

CPI (Consumer Price Index), which measures the price of a selection of goods purchased by a "typical consumer", is a measure of inflation. This is a kind of vague variable due to the complexity of inflation's effect on the economy. Inflation is also viewed as a hidden risk pressure which provides an incentive for those with savings to invest them, rather than have the purchasing power of those savings erode through inflation. In general, when inflation is increasing, this hidden risk pressure will stimulate people to take on extra risk to invest, therefore, it develops a relationship with default probability in this way.

Interest rates, in economic theory, represent the price of hired capital. Therefore, a rise in interest rates should price some borrowers out of the market. The ranks of companies priced out in this manner are more likely not to be able to satisfy their current obligations without obtaining new credit or additional capital. I choose **interest rate spread** because the yield curve is an important indicator of future real activity, according to the expectation theory. When there’s a positively sloping yield increase in the spread between short and long-term interest rates, people expect the market to grow, demand will increase, the economy will be better, banks will have stronger incentives to renegotiate loan terms of certain company, which might result in a decrease of default. Fama (1984), Mankiw and Miron (1986) all find strong predictive power of the term structure regarding the future economic activities. Campbell and Shiller (1987) found evidence that term structure provide useful information about the interest rate evolution. More recently, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) studied the relationship between the term structure and the real economic activity and showed that the slope of the yield curve can predict cumulative changes in real output. Moreover, when Spread goes up, the short interest rate goes up. Hence, it will result in an increase in the future capital cost and an increase of EDF.

The simple intuition behind choosing the **Share Price** can be concluded as follows: Share Price Index represents the performance of the whole stock market, as a proxy, it therefore reflects investors’ sentiment on the state of the economy.

Unemployment is another main economic indicator that is taken into account. When unemployment is high, it causes a lot of downside problems to the economy and the whole society. Therefore, it might associate with an increase of default rates.

Since Sweden is a small and open economy, the **exchange rate** affects the firm's performance in one way or another. I decided to include it as the last indicator in my modeling. Table 6 describes all the macro factors I use.

Variables	Type	Source	Description
Industrial Production	Monthly	OECD	Shown as seasonally adjusted indices. Industrial production refers to the goods produced by establishments engaged in mining (including oil extraction), manufacturing, and production of electricity, gas and water.
CPI	Monthly	OECD	CPIs are a general measure of inflation.
Unemployment Rate[11] (seasonally adjusted)	Monthly	Sweden's Statistical Database	unemployment rates give the numbers of unemployed persons as a percentage of the civilian labor force
Interest Rate Spread	Monthly		Simply the difference between Long-Term Interest Rate and Short-Term Interest Rate
Share Prices	Monthly	OECD	Refer most frequently to "all shares". Monthly data are averages of daily quotations, quarterly and annual data are averages of monthly figures
Exchange Rate	Monthly	OECD	present daily averages of spot rates quoted for the US dollar on national markets expressed as national currency unit per US dollar
Supplementary Variables			
Short-Term Interest Rate	Monthly	OECD & Swedish Central Bank	short-term rates generally refer to three month interbank offer rate attached to loans given and taken
Long-Term Interest Rate	Monthly	OECD	long term rates (in most cases 10 year) generally refer to secondary market yields on long term bonds

Table 6 Independent Variables and Macro Economic Indicators

[11] Unemployment Rate of Sweden from April 2005 to September 2005 are not available at the time of writing this thesis

From the graphs of the macro factors of Sweden, which are displayed in figure 5, most of the macro factors have certain development overtime. Some of them are quite similar due to the correlation between those macro factors. As, all the macro factors are monthly time series data, the analysis could suffer from non stationarity. However, the study period is not long and the variables are all macro factors, so they might not display many changes and hence be stationary. Therefore, some stricter stationarity test has to be carried out.

5.1.3 Stationarity Tests

There are basically three ways of testing the stationarity. The graphical analysis, the correlogram test, and the unit root test. The results concluded from the sequence chart as well as the autocorrelation function (ACF) and partial autocorrelation function (PACF) are coherent showing the non stationarity of all the macro variables. The ACF and PACF of industrial Production of Sweden is shown in the Appendix.

The Dickey-Fuller Unit Root Test is carried out as follows:

$$\Delta Y_t = \delta Y_{t-1} + u_t$$

$H_0 : \delta = 0$, if $\delta = 0$, that is there's a unit root, the time series is nonstationary

If the t-value is significant at 5% level, we reject the null hypothesis and the variable is stationary. The full results from SPSS are displayed in Appendix. The summary of the unit root test is shown in table 7.

Variables	EDF	Industry Production	Spread	Unemployment Rate	CPI	Share Prices	Exchange Rate
Conclusion	Stationary	Not Stationary	Not Stationary	Not Stationary	Not Stationary	Not Stationary	Not Stationary

Table 7 Summary of Unit Root Test

As shown above, all the explanatory variables are not stationary. In order to prevent any impact on the study, I will therefore take the first difference of them in the model, so as to remove the trend in each of the non-stationary variables.

5.2 Method

In order to analyze the relationship between industrial EDF and macro economy, a multifactor Fixed Effect Regression Model, also known as Least-Square Dummy Variable Model (LSDV), is chosen. We chose this model in order to take into account the individuality of each industry. This model makes possible the analysis of the relationship between probability of default and macro economy. It works under the assumption that the macro factors' influence on each industry stays the same over time. Dummies are created according to the number of studied industries in the country. For example, in Sweden, the studied industries for the industry median EDF are Banks, Constructions, Agriculture, Mining, Manufacture, Retail/Wholesale, Transport, Real Estate, Service, Financial, and Others. In order to avoid the dummy trap, 10 dummy variables representing the different industries are created. The model is displayed as:

$$\ln PD_{i,t} = \alpha_0 + \sum_i \alpha_i \cdot D_i + \beta \cdot \ln IP_t + \gamma \cdot \ln SPREAD_t + \delta \cdot \ln SP_t + \varepsilon \cdot \ln CPI_t + \varphi \cdot \ln UR_t + \lambda \cdot \ln EX_t + \upsilon_{i,t}$$

Where

$PD_{i,t}$ Is the probability of default (EDF) of the given industry over time

D_i Is the dummy variable for certain industry. It equals one when the data belongs to the denoted industry, 0 otherwise

$\upsilon_{i,t}$ Is a random variable assumed to be independent and identically normally distributed, $\upsilon_{i,t} \sim N(0, \sigma_i)$

i Denotes a certain industry

t Is the time

A log-linear model is used in order to capture the percentage changes instead of the normal unit changes. First difference is taken for the variables that are not stationary.

6 Empirical Results and Analysis

6.1 Results for Sweden

The empirical study starts with taking all the variables into account and running a mixed linear regression, taking industry as a factor. Half of all the macro factors are significant. Removing all the variables that don't have explanatory power, the results from the final model is shown in the table below. The variables that are significant at 5% level are Industrial Production, Interest Rate Spread and Exchange rate.

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.014293	.085753	686.000	-.167	.868	-.182663	.154078
[Indu=agriculture]	-.909863	.121273	686.000	-7.503	.000	-1.147975	-.671752
[Indu=banks]	-2.739581	.121779	686.000	-22.496	.000	-2.978686	-2.500476
[Indu=construction]	-.896749	.121273	686.000	-7.394	.000	-1.134860	-.658638
[Indu=Financial]	-1.809685	.121273	686.000	-14.922	.000	-2.047797	-1.571574
[Indu=Manufacture	-.608425	.121273	686.000	-5.017	.000	-.846536	-.370313
[Indu=Minning]	-.877661	.122782	686.000	-7.148	.000	-1.118734	-.636588
[Indu=Others]	-.822074	.121273	686.000	-6.779	.000	-1.060185	-.583963
[Indu=Realestate]	-1.463486	.121273	686.000	-12.068	.000	-1.701598	-1.225375
[Indu=Retail]	-.827301	.121273	686.000	-6.822	.000	-1.065412	-.589189
[Indu=Services]	.767227	.121273	686.000	6.326	.000	.529115	1.005338
[Indu=Transport]	0^a	0	.	.	.	.	.
DLnIP	-4.143051	1.805799	686.000	-2.294	.022	-7.688609	-.597494
DLnSpread	1.024382	.201461	686.000	5.085	.000	.628828	1.419935
DLnExch	-5.887470	.874362	686.000	-6.733	.000	-7.604216	-4.170724

Table 8 Estimates of Fixed Effects for industry median EDFs

The coefficients can be understood as, e.g., if Industrial Production increases by 1%, the probability of default which is represented by EDF as dependent variable in the model will on average decrease by 4.143051% holding other variables constant. The coefficients of other variables are interpreted in the same way.

In order to get a measure of "goodness of fit", we calculated the coefficient of determination R^2 with the provided information from the regression. Its value is 0.6284 which means around 63% of the total variation in EDF is explained by this regression model. Most of the signs of the coefficients of the exogenous variables are, where significant, as expected. Higher Industrial Production results in lower default rate and lower EDFs. The effect of the exchange rate on the probability of default depends highly on industries. Indeed, when the exchange rate goes up, importing becomes more expensive, exporting becomes easier, and then fewer competitors in an international arena will result in a decrease of default of national companies.

The positive sign of interest rate spread is arguable, since the positive slope of the interest rate spread usually indicates a "good time" in the economy in the future and therefore a lower probability of default. However, the increase of Spread also reflects the increase of the opportunity cost of future investment. Therefore, it has an opposite impact on EDF. Since this is a monthly analysis, a rational explanation could be the lag impact of the general economy on EDF, as well as the direct and sensitive reaction on the short term interest rate. Regression shows that the Spread six months earlier will have a negative[12] impact on EDF. The table below shows the result of the regression taking both Spread and lagSpread six months. Looking at the coefficients, we notice that the positive effect of the Spread is more than double the lagged negative effect on the EDF. Therefore, even though the spread has a negative effect on the EDF, through the explanation from the general economy, the impact is very small.

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.022554	.087916	657.000	-.257	.798	-.195184	.150077
[Indu=agriculture]	-.924379	.124319	657.000	-7.436	.000	-1.168489	-.680269
[Indu=banks]	-2.773815	.128295	657.000	-21.621	.000	-3.025732	-2.521898
[Indu=construction]	-.895542	.124319	657.000	-7.204	.000	-1.139652	-.651433
[Indu=Financial]	-1.817849	.124319	657.000	-14.623	.000	-2.061959	-1.573739
[Indu=Manufacture	-.603523	.124319	657.000	-4.855	.000	-.847633	-.359413
[Indu=Minning]	-.892291	.125917	657.000	-7.086	.000	-1.139540	-.645043
[Indu=Others]	-.830185	.124319	657.000	-6.678	.000	-1.074295	-.586076
[Indu=Realestate]	-1.459029	.124319	657.000	-11.736	.000	-1.703139	-1.214920
[Indu=Retail]	-.838656	.124319	657.000	-6.746	.000	-1.082766	-.594546
[Indu=Services]	.761961	.124319	657.000	6.129	.000	.517852	1.006071
[Indu=Transport]	0[a]	0	.	.	.	.	.
DLnIP	-3.407879	1.850850	657.000	-1.841	.066	-7.042174	.226416
DLnExch	-6.365216	.984328	657	-6.467	.000	-8.298025	-4.432407
DL6LnSpread	-.477991	.218066	657	-2.192	.029	-.906182	-.049800
DLnSpread	1.083115	.204287	657.000	5.302	.000	.681982	1.484248

Table 9 Estimates of Fixed Effects with LagSpread

[12] Negative here means the coefficient is negative, the spread six months earlier moves in the opposite direction as EDF.

We notice that different macro factors have different amplitude of effects on the probability of default. For instance, the impact of Spread is the lowest among all explanatory variables. There's also a difference in the intercept of each industry. This difference in coefficient between each country can give an insight to the different average level of probability of default within different industries. The final intercept for a given industry is calculated as the sum of the model intercept and the estimated intercept for each industry. The calculation is as follows: e.g. the intercept for mining is the sum of the estimated intercept of the model and the estimated coefficient of mining industry: -0.01429 + (-0.87766) = -0.892 (Based on the result from Table 8). The coefficients for all the industries are summarized in the table below.

Industry	**agri**	**bak**	**cons**	**fin**	**manu**	**trans**
Coefficient	-0.924	-2.754	-0.911	-1.824	-0.623	-0.014
Industry	**min**	**others**	**rest**	**sale**	**serv**	
Coefficient	-0.892	-0.836	-1.478	-0.842	0.753	

Table 10 Summary of the coefficient of each industry (Industry Median EDF, Sweden)

Taking the exponentials of each coefficient, we will get the probability of each industry. The figures are summarized in the table below, which means the baseline probability of the industry if no change occurs for explanatory variables.

Industry	**agri**	**bak**	**cons**	**fin**	**manu**	**trans**
Probability	0.40%	0.06%	0.40%	0.16%	0.54%	0.99%
Industry	**min**	**others**	**rest**	**sale**	**serv**	
Probability	0.41%	0.43%	0.23%	0.43%	2.21%	

Table 11 The probability of each industry

The results are coherent with the graphical analysis in the data description section: service industry followed by transportation has the highest probability of default, leaving banks and financial sectors as the ones having the lowest probability of default. The figures in Table 11 are more or less congruent with the average of the EDF of each industry.

Different industries may react differently to the same economic changes, as it can be seen in the graphs. However, from this model, only one result can be generated, which is how the

EDF as a probability of default will vary with the changes of the macro factor, but this result is not industry specific. We will carry this industry specific analysis in section 6.2.

The same analysis was carried out for EDF 25 as well as EDF 75, which represent the EDFs for the worse 25% companies in the industry and 25% best company in the industry respectively. The data for EDF 25 and 75 is not available for all the industries. The study only includes the following industries: construction, manufacture, retail/wholesale, transport, real estate, services, financial and others. The result from SPSS are shown as below in Tables 12 and 13.

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	1.911525	.092270	500.000	20.717	.000	1.730240	2.092809
[Industry=construction]	-1.868173	.131034	500.000	-14.257	.000	-2.125618	-1.610728
[Industry=Financial]	-1.493238	.130479	500.000	-11.444	.000	-1.749593	-1.236884
[Industry=Manufacture	-1.128583	.130479	500.000	-8.650	.000	-1.384938	-.872228
[Industry=Others]	-.878326	.130479	500.000	-6.732	.000	-1.134681	-.621971
[Industry=Realestate]	-2.144716	.130479	500.000	-16.437	.000	-2.401071	-1.888361
[Industry=Retail]	-1.433379	.130479	500.000	-10.986	.000	-1.689734	-1.177025
[Industry=Services]	-.152858	.130479	500.000	-1.172	.242	-.409213	.103497
[Industry=Transport]	0^a	0	.	.	.	.	.
DLNSpread	1.351094	.250267	500	5.399	.000	.859389	1.842799
DLNSP	-3.076883	.564088	500.000	-5.455	.000	-4.185157	-1.968608
DLNExch	-6.793231	1.084769	500.000	-6.262	.000	-8.924498	-4.661963

Table 12 Estimates of Fixed Effects (a) for EDF 25%

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-1.209608	.075223	500.000	-16.080	.000	-1.357400	-1.061816
[Indu=construction]	-.861629	.106825	500.000	-8.066	.000	-1.071510	-.651747
[Indu=Financial]	-2.037320	.106373	500.000	-19.153	.000	-2.246313	-1.828327
[Indu=Manufacture	-.857130	.106373	500.000	-8.058	.000	-1.066123	-.648137
[Indu=Others]	-1.183669	.106373	500.000	-11.128	.000	-1.392662	-.974677
[Indu=Realestate]	-1.193448	.106373	500.000	-11.219	.000	-1.402440	-.984455
[Indu=Retail]	-.819483	.106373	500.000	-7.704	.000	-1.028476	-.610491
[Indu=Services]	.707646	.106373	500.000	6.653	.000	.498654	.916639
[Indu=Transport]	0^a	0	.	.	.	.	.
DLnExch	-4.988429	.884355	500.000	-5.641	.000	-6.725939	-3.250918
DLNSpread	1.075417	.204030	500	5.271	.000	.674555	1.476278
DLNSP	-1.815836	.459871	500	-3.949	.000	-2.719354	-.912319

Table 13 Estimates of Fixed Effects for EDF 75%

The variables significant this time are: Spread, Share Price and Exchange Rate, for both EDF 25 and EDF 75, which differs from that of EDF 50. However, signs are as expected. Table 14 summarizes the coefficients of the macro variables in all three regressions.

	Industry Production	Spread	Exchange Rate	Share Price
EDF 25%		1.351094	-6.793231	-3.076883
EDF 50%	-4.143051	1.024382	-5.887470	
EDF 75%		1.075417	-4.988429	-1.815836

Table 14 Summary of coefficient of macro factors

From the table above, three conclusions can be generated. For Sweden, changes in macro factors such as Industrial Production, Spread, Exchange Rate and Share Price affect the probability of default. Second, the different macro factors have different influence on probability of default, e.g. Exchange Rate in general has a larger influence than the others, and Spread has the least influence. Finally, the sensitivity of the industry EDFs towards the changes in macro factors varies with the quality of the company. The better the company, the less their probability of default will vary with the macro factor changes. For EDF 25% representing the worse 25% of the company in the industry, they are in general more influenced by the state of the economy. If exchange rate increases by 1%, holding other variables constant, EDF 25 on average will decrease by 6.793231%, whereas EDF 50 and 75 decrease by 5.887470% and 4.988429% respectively.

6.2 Sensitivity Analysis

As stated before, the result is not yet completely satisfying, since the graphical analysis shows that EDF of the given industries vary with different amplitude to the same changes in the macro conditions. This might be explained by the way each industry is tied to the general economy as well as by the contagious risk within each industry. Therefore, our model has to be improved. The following new proposed model makes it possible to take into account the sensitivity of the given industries with the changes of macro factors.

$$LnPD_{i,t} = \alpha_0 + \sum_i \alpha_i D_i + \left(\beta_0 + \sum_i \beta_i D_i\right) LnIP_t + \left(\gamma_0 + \sum_i \gamma_i D_i\right) LnSPREAD_t + \left(\lambda_0 + \sum_i \lambda_i D_i\right) LnExch + \upsilon_{i,t}$$

Industry	IP	Spread	Exchange
Agriculture	-8.13716	0.720761	-3.58746
Banks	-3.8296	0.497664	-0.34907
Construction	-4.60042	1.402103	-8.33197
Financial	-6.28749	1.372262	-5.37096
Manufacture	-1.57001	1.048295	-6.14449
Mining	-9.43187	0.74269	-0.8093
Others	-1.10706	1.438073	-11.5415
Real Estate	-8.02843	0.504717	0.685904
Retail/Wholesale	-3.81225	1.143144	-8.16238
Service	-1.47003	1.862433	-13.9547
Transportation	-4.66032	0.423138	-3.76749

Table 15 Summary of coefficients of different industries

The result from SPSS is displayed in Appendix. The summary of the coefficients of the studied industries is provided in the table above. In this table, each coefficient can be interpreted in the following way: if Industrial Production increases by 1%, holding other variables constant, how much the EDF of each industry would change on average. A similar interpretation goes for Exchange Rate as well as for Interest Rate Spread. Agriculture and Mining are the industries most sensitive towards the changes in Industrial Production: when IP increases by 1%, the EDFs of these two industries decrease by 8.13716% and 9.43187% respectively. As for the impact of Exchange Rate, the effects vary according to each industry. Indeed, when the Exchange Rate goes up, it's more expensive to import, and cheaper to export. Therefore, there will be fewer competitors on the international market for the national company, which will mean a decrease of EDF on certain industries. Exchange Rate has more influence on Service, Retail/Wholesale and Construction. More specifically, when Exchange Rate increases by 1%, the EDF of Service industry will decrease by 13.9547% whereas the bank, which is the least sensitive towards Exchange Rate changes, only decreases by 0.34907%. Most of the coefficients of the differences are not significant at 5% level apart from a few in the exchange rate variables. This could be explained as no significant differences from the base industry. Since the model took the first difference of the variables, this result is not really surprising.

6.3 Results on other European Countries and US

We will now present the same kind of analysis for other countries as a comparison with Sweden. When running regressions for other European Countries and the US, it is interesting to find out that the effect of macro economic factors on EDFs are country specific. Most of the signs of the coefficient for the macro factors are as expected. The effects of macro factors in general are less in Finland and UK. The default probabilities in the US are more influenced by macro variables when compared to other countries. Industrial Production is not significant in most of the countries other than Sweden and the US. In contrary to Sweden, the effect of Industrial Production in the US is quite huge comparing with other explanatory variables. When other variables stay the same, if industrial production in the US grows by 1%, the probability of default on average will decrease by 14.4832%. The effect of Spread on the probability of default in the US is double than that of other countries. The CPI is always a factor that can have huge influence on the probability of default. In Norway, Germany and the US, when CPI increases by 1%, the probability of default will on average decrease by 42.6766%, 14.3733% and 29.9402%, which are all much larger than the influence caused by other macro variables. When comparing with other variables, the influence of Spread is usually very small. The results of the regressions are shown in the tables in the Appendix.

Analyses of the sensitivity of industries' EDF to the changes in macro factors for these countries were carried out. Detailed results from the regressions are presented in Appendix, the table summary of the entire industries' coefficients are shown below. As a summary, it is hard to conclude which industry or industries are the least influenced ones when it comes to macro changes. It depends on the country, the industry as well as macro factor. Spread has the least influence on the industries in all given countries.

	Unemployment Rate	Share Price	Exchange
bak	3.45223	-4.9079	2.40132
cons	6.17922	-1.33234	-7.29167
fin	2.23284	-3.20362	-0.54839
manu	6.43774	-3.89171	-4.96272
other	5.02986	-2.93623	-4.71758
rest	5.30702	-5.23684	-0.63374
sale	6.83374	-6.06309	-5.53259
serv	5.42862	-2.39420	-5.37044
trans	3.58464	-2.94356	-0.39982

Table 16 Coefficient Summary Denmark

	Spread	CPI	SP	Exchange
bak	0.0827	-14.61	-2.4129	-0.87775
fin	0.202	-26.35	-2.7202	-1.73886
manu	0.6805	-50.87	-3.8416	-6.30605
other	0.9868	-72.28	-1.5237	-7.17123
rest	0.2453	-29.88	-0.004	-3.26878
sale	0.4701	-33.85	-2.7437	-4.5051
serv	0.6895	-50.68	-3.8801	-5.08279
trans	0.6241	-51.64	-6.9231	-3.39043

Table 17 Coefficient Summary Norway

	bak	cons	fin	manu	rest	sale	serv	trans
Spread	-0.702	0.4988	0.5411	0.9451	0.4749	0.4498	0.5124	0.1642
Share Price	0.9275	-0.594	-0.167	-1.376	-0.241	-0.916	-0.943	-0.182

Table 18 Coefficient Summary Finland

	agri	bak	cons	fin	manu	other	rest	sale	serv	trans
Spread	0.433	0.058	0.191	0.110	0.201	0.274	0.248	0.181	0.123	0.231
Share Price	-0.233	-1.650	-2.064	-3.674	-1.947	-2.695	0.239	-3.168	-2.130	-1.248

Table 19 Coefficient Summary UK

	Spread	Unemployment Rate	CPI	Exchange
agri	0.283084	6.827412	-26.835734	-8.5925344
bak	0.248923	-0.70762	1.2757304	-3.3153904
cons	-0.01575	6.51739	-19.823773	-1.4340982
fin	0.194964	1.612838	-3.9691054	-4.8441414
manu	0.18835	5.283651	-18.473765	-5.033413
other	0.704825	8.529788	-23.374492	-13.665378
rest	0.16345	3.237345	-11.592109	-3.5097345
sale	0.18408	4.99952	-15.137596	-3.9923901
serv	0.636731	7.321186	-14.674242	-10.683944
trans	0.01789	2.867313	-12.774987	-3.5395914

Table 20Coefficient Summary Germany

	IP	Spread	Unemployment Rate	CPI	Share Price
bak	-13.484399	1.0973151	5.2323017	-22.20372	-3.7237209
fin	-11.871014	1.353423	5.7070955	-28.980322	-4.298532
rest	-18.094287	2.126382	8.9260686	-38.63651	-5.5413994

Table 21 Coefficient Summary US

7 Conclusion and Suggestions for further research

This paper has analyzed the relationship of Macro Economic Factors with the Probability of Default on an industrial level. Data for both EDF and the macro economic factors are all on a monthly basis, from April 2000 to September 2005. Using the multifactor fixed effect model, the study verified the effect of macro factors on probability of default, and furthermore analyzed it quantitatively. Several results have been found out. In Sweden, changes in macro factors such as Industrial Production, Interest Rate Spread, Exchange Rate, and Share Price affect the probability of default (However, this result cannot be generalized to other countries, since this impact varies with countries). All macro factors have a different influence on probability of default. Exchange Rate has much higher influence when compared to others, whereas the Spread has the least impact. The sensitivity towards the effects of macro economy varies with the quality of the company, since results from analyzing EDF 25 and EDF 75 show that, the better the company, the less it is influenced by macro changes.

Evidence also showed that industries react to the same macro changes with different amplitude.

The study was carried out for Sweden mainly. However, research has been done on other countries such as Denmark, Norway, Finland, UK, Germany, and the US. So far the results are encouraging in terms of both statistical fit and model usefulness (normality test, heteroscedasticity test and autocorrelation test were all carried out and no problem has been detected), yet, the model could benefit from having longer time series covering a full macroeconomic cycle.

This study can be useful for credit risk managers in commercial banks and help them answer questions like “what would be the impact on the risk profile of a certain industry in a given region if industrial production or interest rates increases?” This thesis would also be a good ground study for people who are interested in:

- Further analyzing the sensitivity of bank portfolios
- Modeling the volatility of EDF on an industry level
- Carrying out scenario shock analysis, i.e. analyzing how a shock to one specific macroeconomic variable affects the risk profile of companies or industries across countries.

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9 Appendix

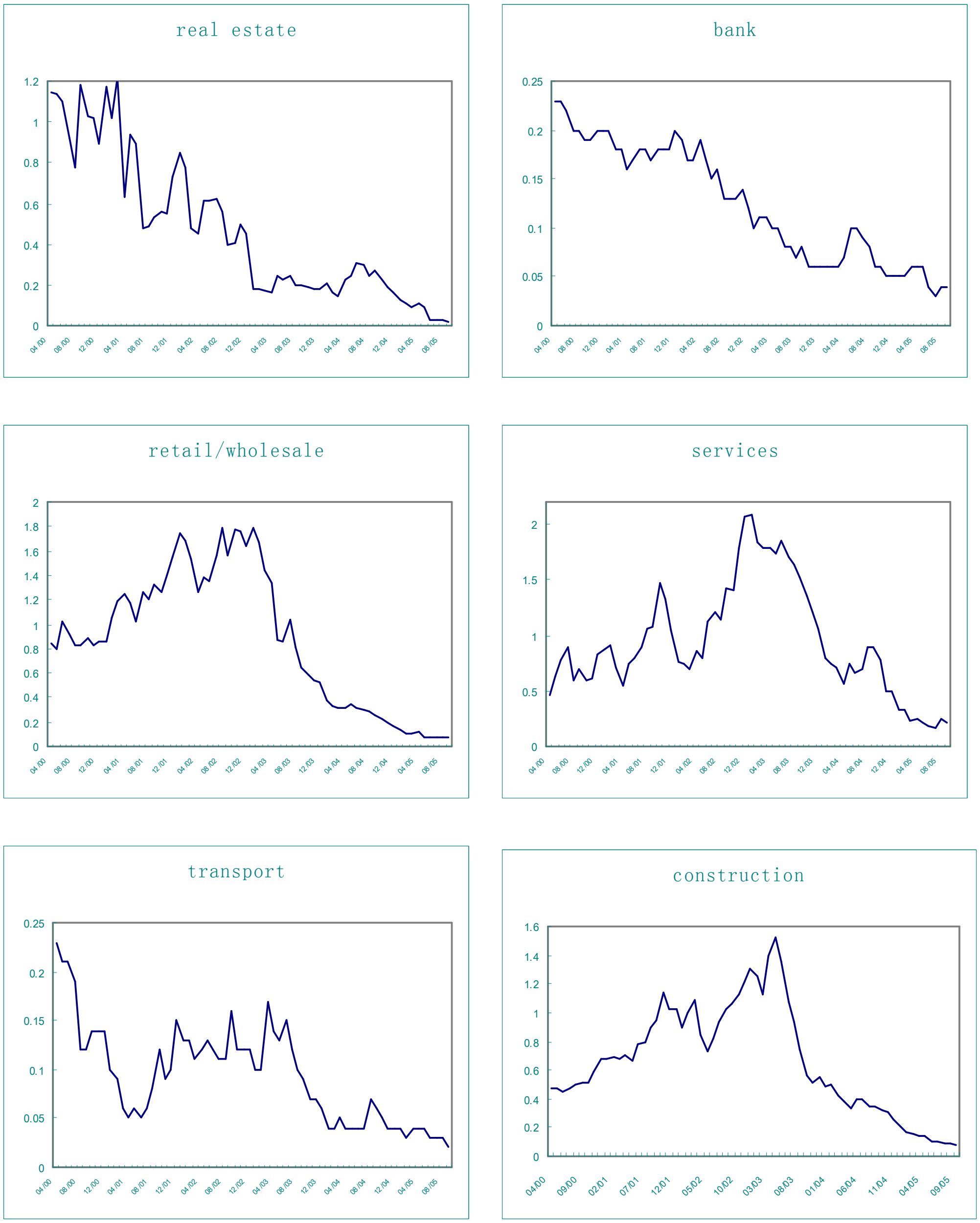


Fig 1 Industrial Median EDFs of Denmark

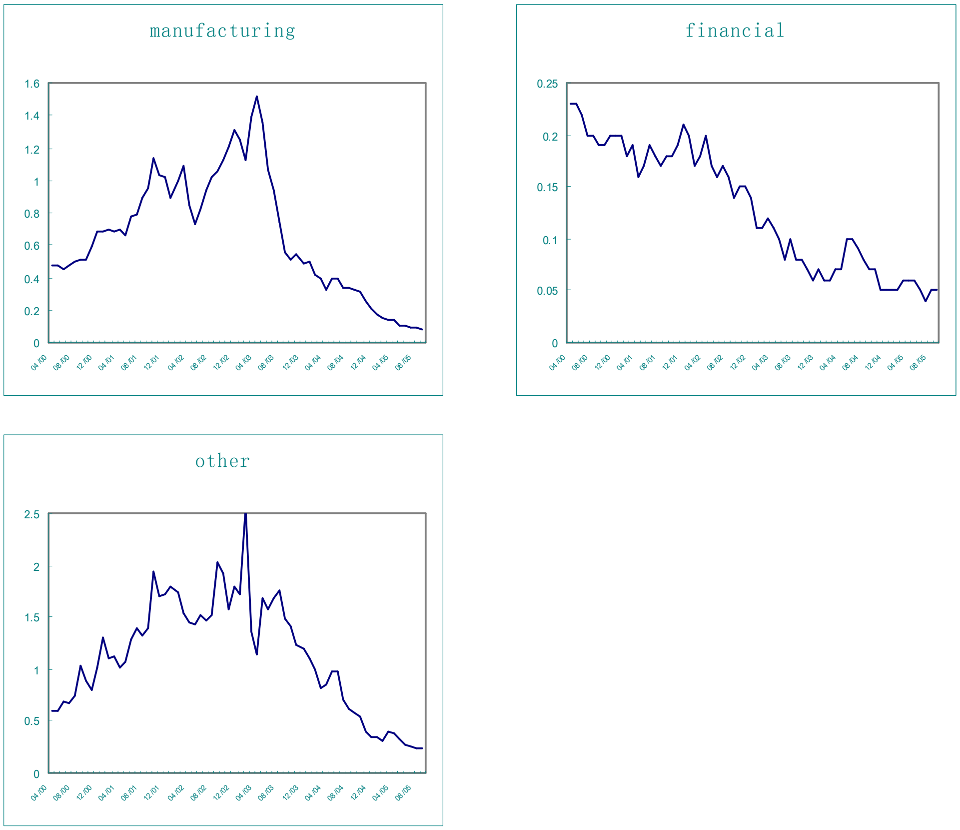
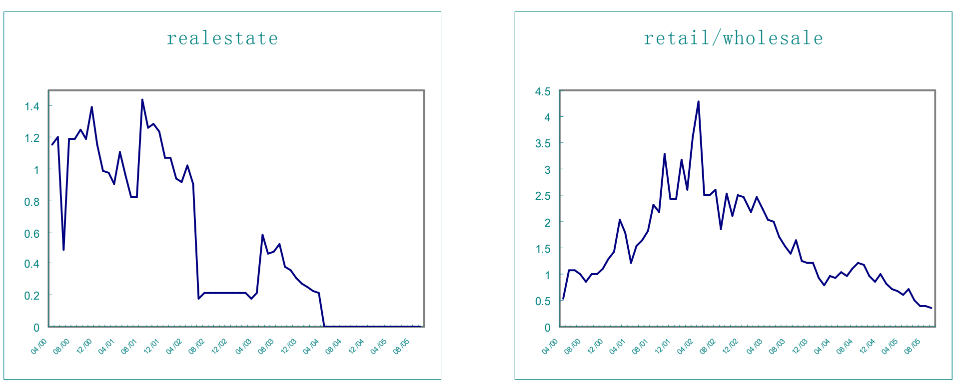


Fig 2 Industrial Median EDFs of Norway



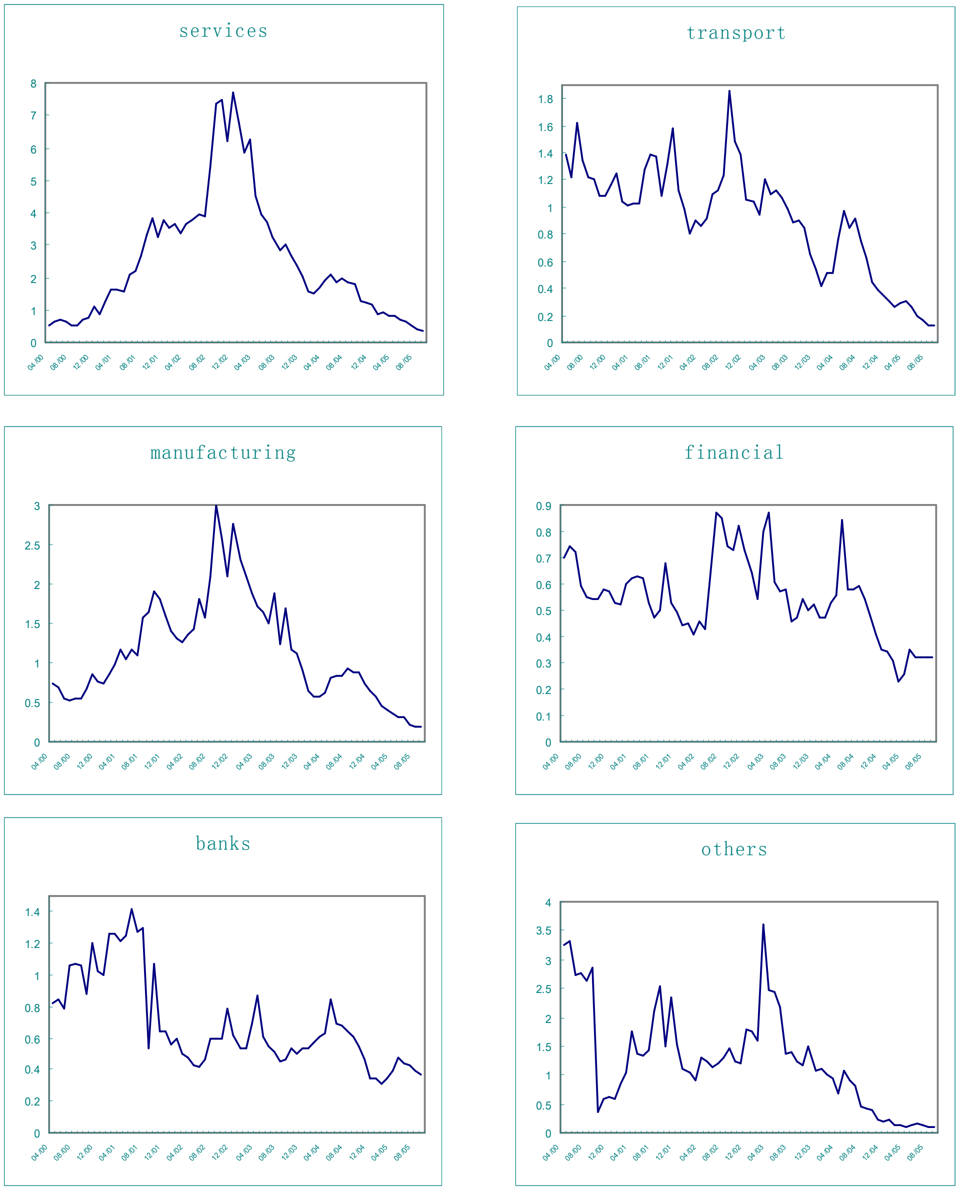
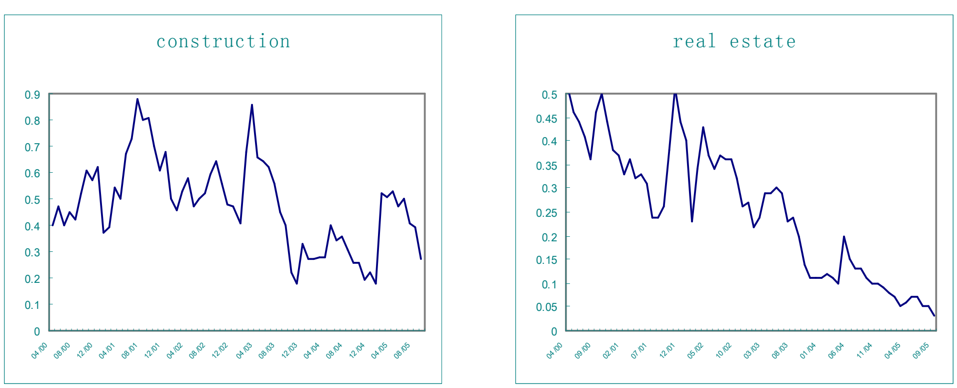
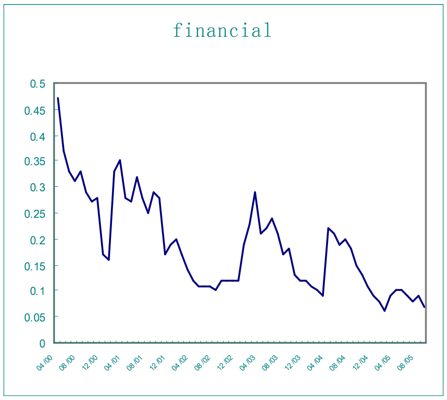


Fig 3 Industrial Median EDFs of Finland

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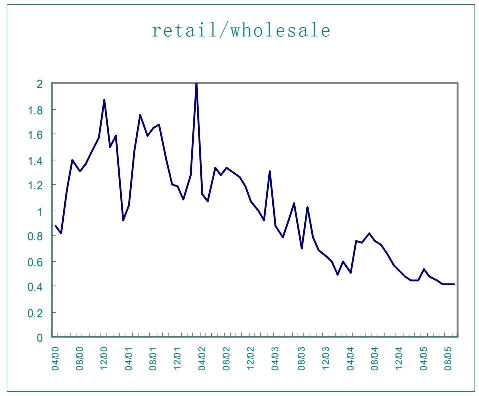
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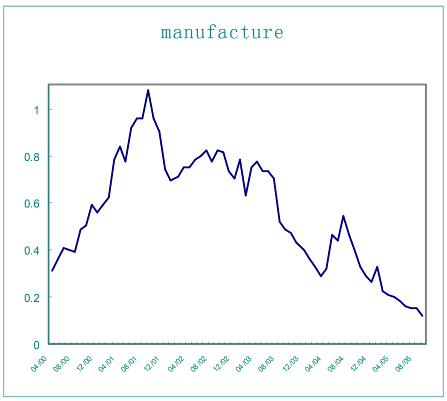
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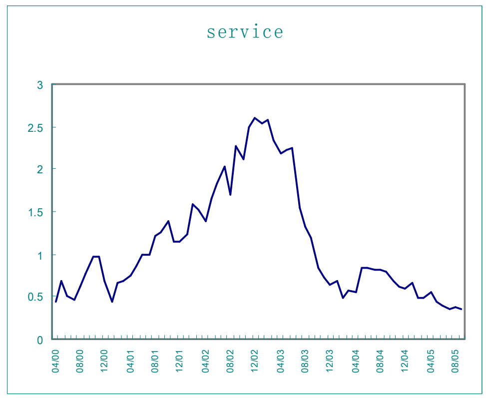
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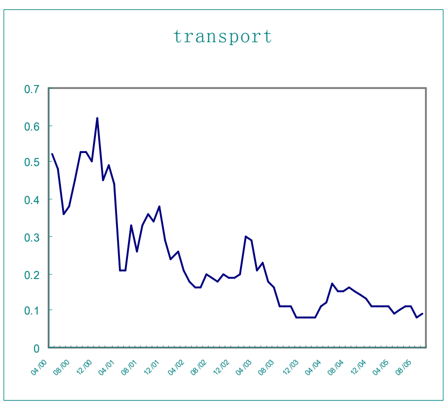
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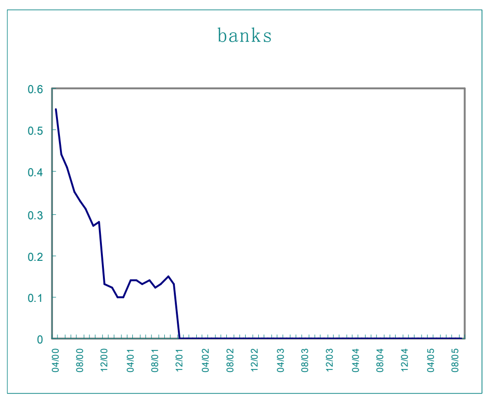
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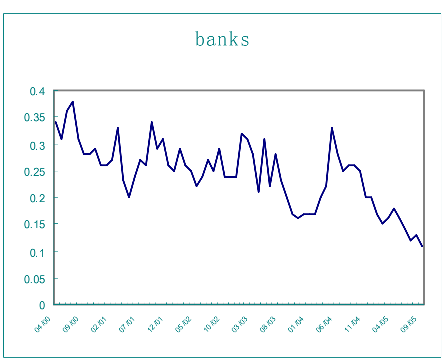
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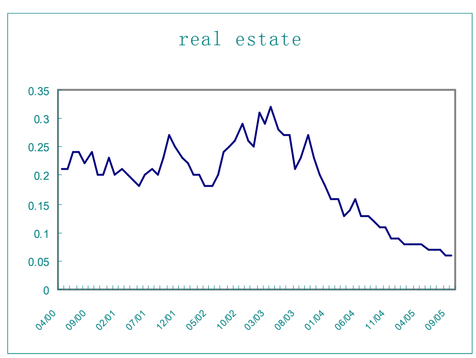
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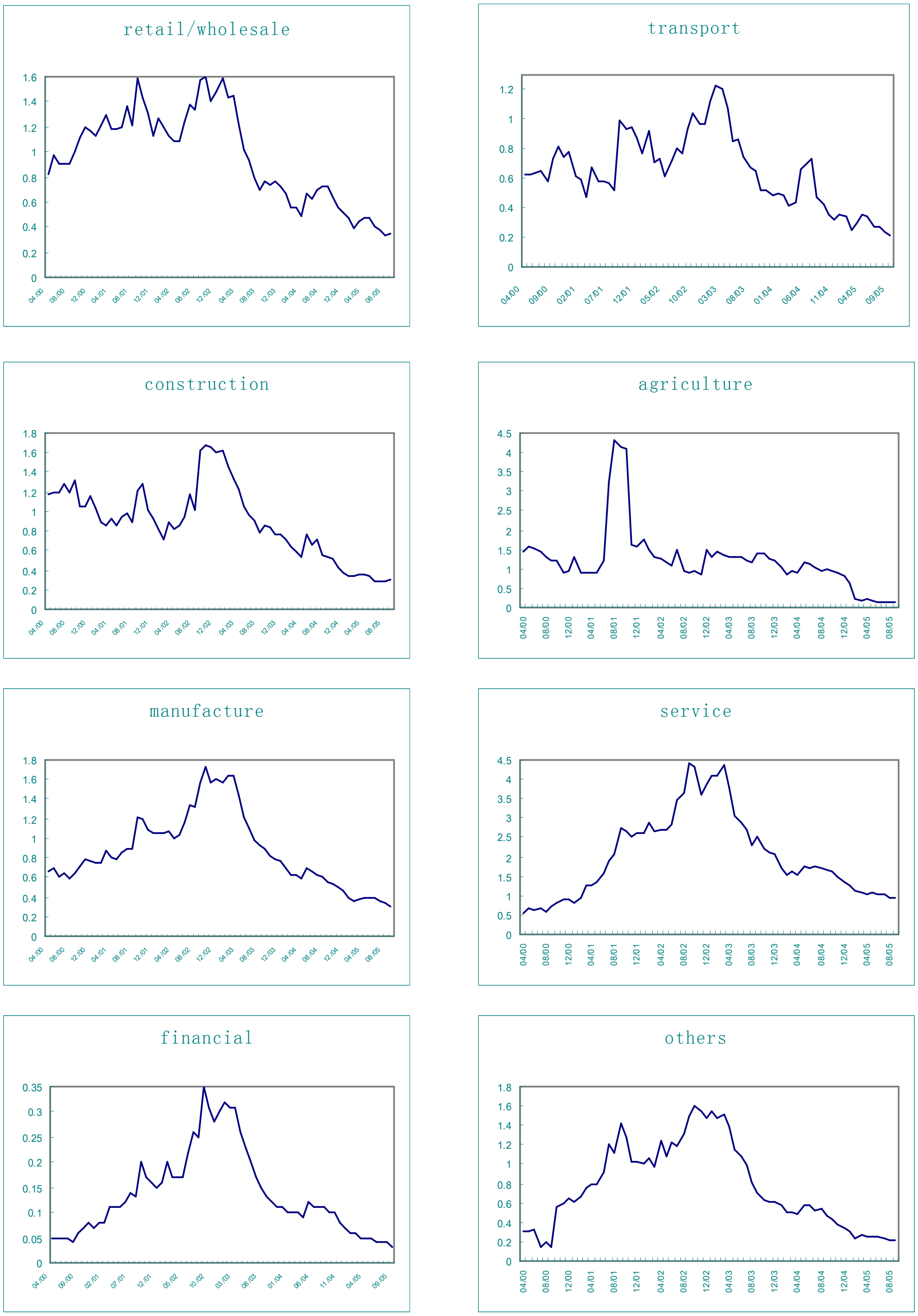
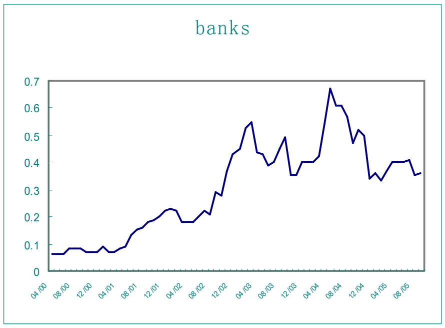


Fig 4 Industry Median EDFs of UK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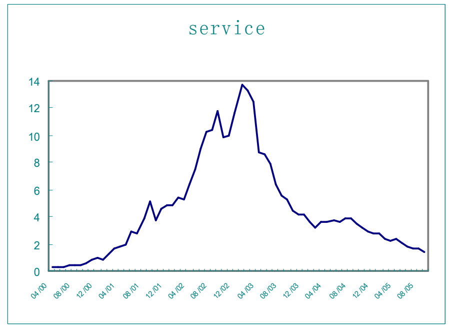
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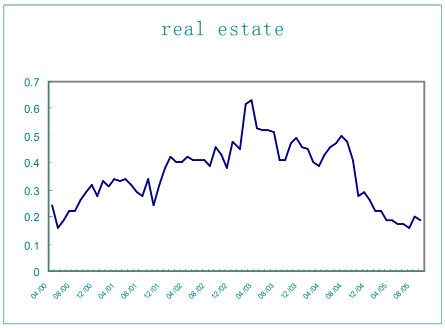
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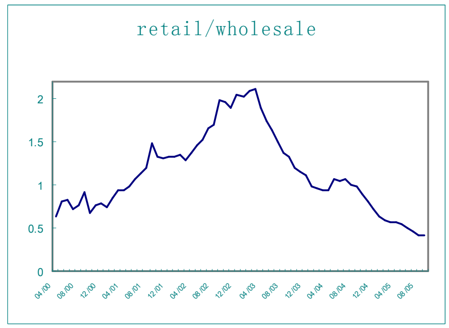
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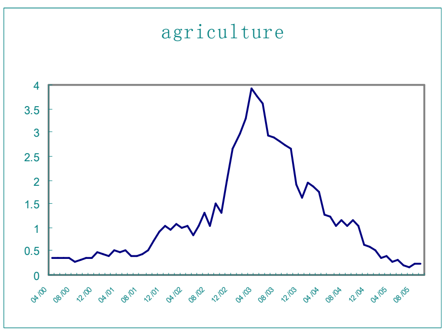
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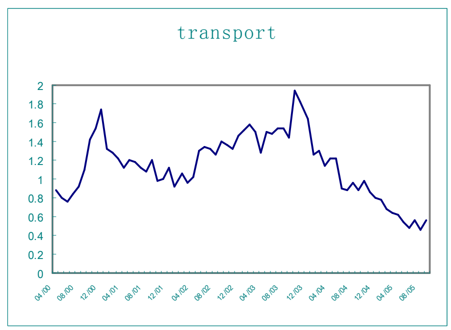
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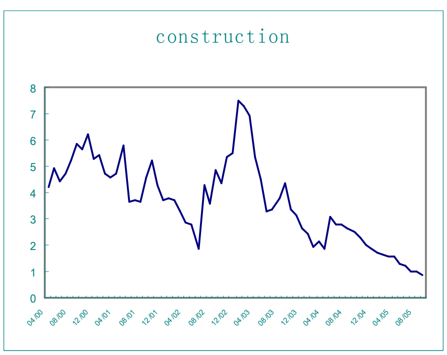
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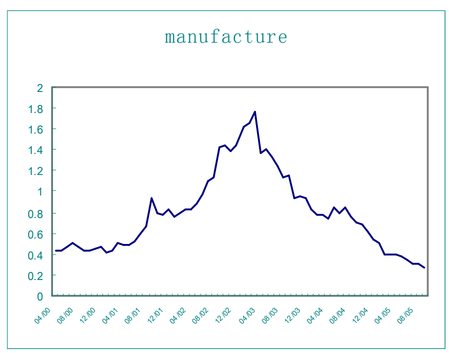
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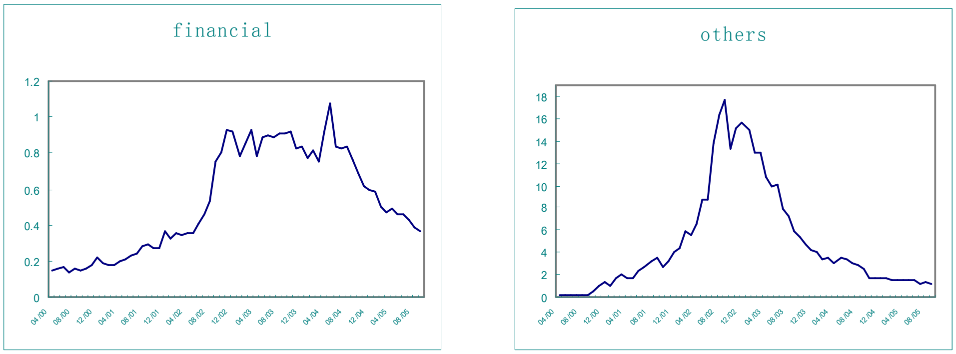

Fig 5 Industry Median EDFs of Germany

Fig 6 Industry Median EDFs of US

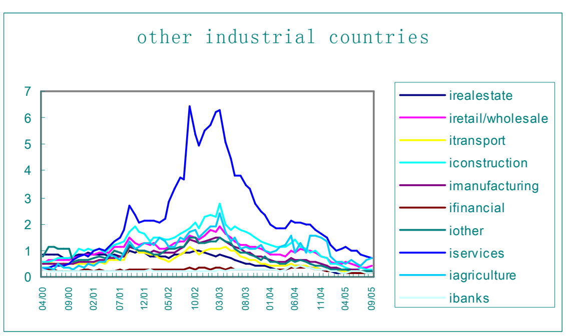

Fig 7 Industry Median EDFs of other industrial countries

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.327	.252		1.299	.199
	LAGS(LnIP,1)	-.071	.055	-.161	-1.295	.200

a. Dependent Variable: DIFF(LnIP,1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.030	.025		1.183	.242
	LAGS(LnSpread,1)	-.080	.050	-.200	-1.590	.117

a. Dependent Variable: DIFF(LnSpread,1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.086	.078		1.104	.274
	LAGS(LnUR,1)	-.050	.046	-.143	-1.093	.279

a. Dependent Variable: DIFF(LnUR,1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.149	.093		1.601	.114
	LAGS(LnCPI,1)	-.032	.020	-.196	-1.588	.117

a. Dependent Variable: DIFF(LnCPI,1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.189	.105		1.799	.077
	LAGS(LnSP,1)	-.047	.025	-.226	-1.843	.070

a. Dependent Variable: DIFF(LnSP,1)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.023	.050		.449	.655
	LAGS(LnExch,1)	-.011	.023	-.062	-.492	.624

a. Dependent Variable: DIFF(LnExch,1)

Table 1 Unit Root tests for the macro factors of Sweden

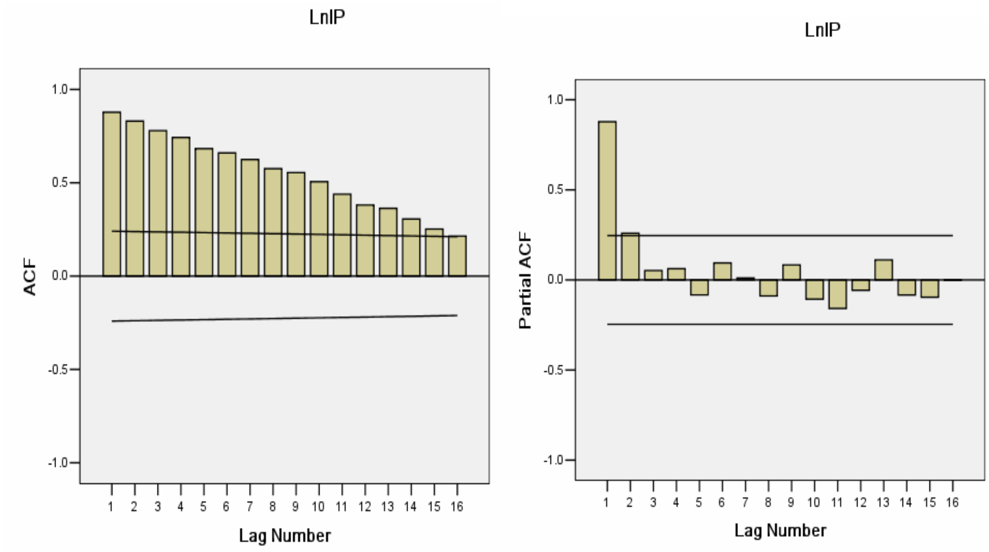

Fig 8 ACF & PACF of IP of Sweden

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.014731	.085509	656.000	-.172	.863	-.182636	.153174
[Indu=agriculture]	-.909954	.120928	656.000	-7.525	.000	-1.147407	-.672501
[Indu=banks]	-2.727356	.121899	656.000	-22.374	.000	-2.966715	-2.487996
[Indu=construction]	-.896085	.120928	656.000	-7.410	.000	-1.133538	-.658632
[Indu=Financial]	-1.809204	.120928	656.000	-14.961	.000	-2.046657	-1.571751
[Indu=Manufacture]	-.607765	.120928	656.000	-5.026	.000	-.845218	-.370312
[Indu=Minning]	-.859868	.122912	656.000	-6.996	.000	-1.101217	-.618519
[Indu=Others]	-.821078	.120928	656.000	-6.790	.000	-1.058532	-.583625
[Indu=Realestate]	-1.463748	.120928	656.000	-12.104	.000	-1.701201	-1.226294
[Indu=Retail]	-.826738	.120928	656.000	-6.837	.000	-1.064191	-.589285
[Indu=Services]	.768484	.120928	656.000	6.355	.000	.531031	1.005937
[Indu=Transport]	0[a]	0	.	.	.	.	.
DLnIP	-4.660321	5.846961	656.000	-.797	.426	-16.141337	6.820695
DLnSpread	.423138	.665344	656.000	.636	.525	-.883323	1.729598
DLnExch	-3.767494	2.838174	656.000	-1.327	.185	-9.340495	1.805507
DLnIP([Indu=agri])	-3.476843	8.268852	656.000	-.420	.674	-19.713451	12.759765
DLnIP([Indu=bak])	.830725	9.154161	656.000	.091	.928	-17.144264	18.805715
DLnIP([Indu=cons])	.059901	8.268852	656.000	.007	.994	-16.176707	16.296510
DLnIP([Indu=fin])	-1.627173	8.268852	656.000	-.197	.844	-17.863781	14.609436
DLnIP([Indu=Manu])	3.090311	8.268852	656.000	.374	.709	-13.146297	19.326919
DLnIP([Indu=Min])	-4.771551	9.185891	656.000	-.519	.604	-22.808846	13.265744
DLnIP([Indu=Other])	3.553264	8.268852	656.000	.430	.668	-12.683344	19.789872
DLnIP([Indu=Rest])	-3.368108	8.268852	656.000	-.407	.684	-19.604716	12.868501
DLnIP([Indu=sale])	.848070	8.268852	656.000	.103	.918	-15.388538	17.084678
DLnIP([Indu=Serv])	3.190288	8.268852	656.000	.386	.700	-13.046320	19.426897
DLnIP([Indu=Trans])	0[a]	0	.	.	.	.	.
DLnSpread([Indu=agri])	.297623	.940939	656.000	.316	.752	-1.549992	2.145238
DLnSpread([Indu=banks])	.074527	.942985	656.000	.079	.937	-1.777107	1.926160
DLnSpread([Indu=cons])	.978965	.940939	656.000	1.040	.299	-.868650	2.826580
DLnSpread([Indu=Fin])	.949124	.940939	656.000	1.009	.313	-.898491	2.796739
DLnSpread([Indu=Manu])	.625157	.940939	656.000	.664	.507	-1.222457	2.472772
DLnSpread([Indu=Min])	.319553	.947840	656.000	.337	.736	-1.541613	2.180719
DLnSpread([Indu=Other])	1.014936	.940939	656.000	1.079	.281	-.832679	2.862550
DLnSpread([Indu=Rest])	.081579	.940939	656.000	.087	.931	-1.766035	1.929194
DLnSpread([Indu=sale])	.720007	.940939	656.000	.765	.444	-1.127608	2.567622
DLnSpread([Indu=Serv])	1.439295	.940939	656.000	1.530	.127	-.408320	3.286910
DLnSpread([Indu=Trans])	0[a]	0	.	.	.	.	.
DLnExch([Indu=agri])	.180033	4.013784	656.000	.045	.964	-7.701380	8.061446
DLnExch([Indu=bak])	3.418420	4.361071	656.000	.784	.433	-5.144921	11.981761
DLnExch([Indu=cons])	-4.564472	4.013784	656.000	-1.137	.256	-12.445885	3.316942
DLnExch([Indu=Fin])	-1.603466	4.013784	656.000	-.399	.690	-9.484879	6.277948
DLnExch([Indu=Manu])	-2.376992	4.013784	656.000	-.592	.554	-10.258405	5.504421
DLnExch([Indu=Min])	2.958190	4.439857	656.000	.666	.505	-5.759856	11.676235
DLnExch([Indu=Other])	-7.773970	4.013784	656.000	-1.937	.053	-15.655383	.107443
DLnExch([Indu=Rest])	4.453399	4.013784	656.000	1.110	.268	-3.428015	12.334812
DLnExch([Indu=sale])	-4.394881	4.013784	656.000	-1.095	.274	-12.276294	3.486532
DLnExch([Indu=Serv])	-10.1872	4.013784	656.000	-2.538	.011	-18.068578	-2.305752
DLnExch([Indu=Trans])	0[a]	0	.	.	.	.	.

Table 2 Estimated Fixed Effect – Sweden

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	-2.533864	.086724	581.000	-29.218	.000	-2.704195	-2.363533
[Indu=banks]	.297382	.123162	581.000	2.415	.016	.055485	.539279
[Indu=construction]	2.645970	.122646	581.000	21.574	.000	2.405086	2.886854
[Indu=Financial]	.356135	.122646	581.000	2.904	.004	.115251	.597019
[Indu=Manufacture	1.892909	.122646	581.000	15.434	.000	1.652025	2.133793
[Indu=Others]	2.489431	.122646	581.000	20.298	.000	2.248547	2.730315
[Indu=Realestate]	1.402098	.122646	581.000	11.432	.000	1.161214	1.642982
[Indu=Retail]	2.055106	.122646	581.000	16.756	.000	1.814222	2.295990
[Indu=Services]	2.301712	.122646	581.000	18.767	.000	2.060828	2.542596
[Indu=Transport]	0[a]	0	.	.	.	.	.
DLNUR	4.882266	.925936	581.000	5.273	.000	3.063676	6.700857
DLNSP	-3.443950	.542930	581.000	-6.343	.000	-4.510295	-2.377606
DLNExch	-3.393481	.891233	581.000	-3.808	.000	-5.143912	-1.643051

Table 3 Estimates of Fixed Effects Denmark

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	-.643539	.114225	202.000	-5.634	.000	-.868765	-.418313
[Indo=bak]	.045210	.141948	202.000	.318	.750	-.234679	.325100
[Indo=fin]	-.070604	.141948	202.000	-.497	.619	-.350493	.209286
[Indo=manu]	.336238	.141948	202.000	2.369	.019	.056348	.616127
[Indo=other]	-.001990	.141948	202.000	-.014	.989	-.281879	.277900
[Indo=rest]	-.421997	.192704	202.000	-2.190	.030	-.801966	-.042028
[Indo=sale]	.656875	.141948	202.000	4.628	.000	.376985	.936764
[Indo=serv]	1.105798	.141948	202.000	7.790	.000	.825909	1.385688
[Indo=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.505950	.088970	202.000	5.687	.000	.330522	.681378
DLNCPI	-42.6766	12.347779	202.000	-3.456	.001	-67.023673	-18.329530
DLNSP	-3.320037	1.215440	202.000	-2.732	.007	-5.716614	-.923459
DLNExch	-4.116475	1.649568	202.000	-2.495	.013	-7.369056	-.863894

Table 4 Estimates of Fixed Effects Norway

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	-1.627925	.065651	471.000	-24.797	.000	-1.756930	-1.498920
[Indu=bak]	-.096036	.139041	471.000	-.691	.490	-.369253	.177180
[Indu=cons]	.826650	.092845	471.000	8.904	.000	.644209	1.009091
[Indu=fin]	-.159958	.092845	471.000	-1.723	.086	-.342400	.022483
[Indu=manu	.923787	.092845	471.000	9.950	.000	.741346	1.106228
[Indu=rest]	.051170	.092845	471.000	.551	.582	-.131271	.233611
[Indu=sale]	1.546269	.092845	471.000	16.654	.000	1.363828	1.728710
[Indu=serv]	1.560622	.092845	471.000	16.809	.000	1.378180	1.743063
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.382852	.126746	471	3.021	.003	.133794	.631910
DLNSP	-.525217	.207424	471	-2.532	.012	-.932808	-.117625

Table 5Estimates of Fixed Effects Finland

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.313255	.050825	358.000	-6.163	.000	-.413209	-.213302
[Indu=agri]	.549954	.071830	358.000	7.656	.000	.408692	.691215
[Indu=bak]	-1.098721	.071830	358.000	-15.296	.000	-1.239982	-.957459
[Indu=cons]	.238665	.071830	358.000	3.323	.001	.097403	.379926
[Indu=fin]	-1.457928	.071830	358.000	-20.297	.000	-1.599189	-1.316666
[Indu=manu	.317838	.071830	358.000	4.425	.000	.176577	.459099
[Indu=other]	.235814	.071830	358	3.283	.001	.094553	.377076
[Indu=rest]	-1.260565	.071830	358	-17.549	.000	-1.401827	-1.119304
[Indu=sale]	.302101	.071830	358.000	4.206	.000	.160840	.443363
[Indu=serv]	1.263768	.071830	358.000	17.594	.000	1.122506	1.405029
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.205363	.033507	358	6.129	.000	.139467	.271259
DLNSP	-1.857219	.457592	358	-4.059	.000	-2.757124	-.957313

Table 6 Estimates of Fixed Effects UK

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.082385	.083665	625.000	.985	.325	-.081914	.246685
[Indu=agri]	-.241301	.118290	625	-2.040	.042	-.473596	-.009006
[Indu=bak]	-1.456830	.118807	625.000	-12.262	.000	-1.690139	-1.223520
[Indu=cons]	1.091085	.118290	625	9.224	.000	.858790	1.323380
[Indu=fin]	-.867907	.118290	625.000	-7.337	.000	-1.100202	-.635612
[Indu=manu	-.413847	.118290	625.000	-3.499	.001	-.646142	-.181552
[Indu=Others]	.953138	.118290	625	8.058	.000	.720843	1.185433
[Indu=rest]	-1.169378	.118290	625.000	-9.886	.000	-1.401673	-.937083
[Indu=sale]	-.034094	.118290	625.000	-.288	.773	-.266389	.198201
[Indu=serv]	1.051492	.118290	625.000	8.889	.000	.819197	1.283787
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.260804	.069051	625.000	3.777	.000	.125203	.396404
DLNUR	4.655714	1.131740	625.000	4.114	.000	2.433240	6.878188
DLNCPI	-14.3733	3.874526	625.000	-3.710	.000	-21.981949	-6.764617
DLNExch	-5.865933	1.055385	625.000	-5.558	.000	-7.938462	-3.793403

Table 7 Estimates of Fixed Effects Germany

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-1.509802	.049621	151	-30.427	.000	-1.607843	-1.411762
[Indu=bak]	-.017538	.063800	151	-.275	.784	-.143593	.108517
[Indu=fin]	.231143	.063800	151	3.623	.000	.105087	.357198
[Indu=rest]	0[a]	0	.	.	.	.	.
DLNSpread	1.525707	.149724	151	10.190	.000	1.229882	1.821531
DLNUR	6.621822	1.145506	151.000	5.781	.000	4.358533	8.885111
DLNCPI	-29.9402	7.945845	151	-3.768	.000	-45.639575	-14.240793
DLNSP	-4.521217	.721430	151	-6.267	.000	-5.946618	-3.095817
DLNIP	-14.4832	5.744328	151	-2.521	.013	-25.832870	-3.133597

Table 8 Estimates of Fixed Effects US

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	-2.533864	.086170	557.000	-29.405	.000	-2.703123	-2.364606
[Indu=banks]	.329667	.124003	557.000	2.659	.008	.086098	.573237
[Indu=construction]	2.645970	.121863	557.000	21.713	.000	2.406602	2.885338
[Indu=Financial]	.356135	.121863	557.000	2.922	.004	.116767	.595502
[Indu=Manufacture]	1.892909	.121863	557.000	15.533	.000	1.653541	2.132277
[Indu=Others]	2.489431	.121863	557.000	20.428	.000	2.250063	2.728798
[Indu=Realestate]	1.402098	.121863	557.000	11.506	.000	1.162731	1.641466
[Indu=Retail]	2.055106	.121863	557.000	16.864	.000	1.815738	2.294474
[Indu=Services]	2.301712	.121863	557.000	18.888	.000	2.062344	2.541080
[Indu=Transport]	0[a]	0	.	.	.	.	.
DLNUR	3.584644	2.759356	557.000	1.299	.194	-1.835372	9.004661
DLNSP	-2.943565	1.603226	557.000	-1.836	.067	-6.092672	.205543
DLNExch	-.399827	2.625953	557.000	-.152	.879	-5.557809	4.758155
DLNUR([Indu=bak])	-.132408	3.921516	557.000	-.034	.973	-7.835175	7.570359
DLNUR([Indu=cons])	2.594581	3.902319	557.000	.665	.506	-5.070480	10.259642
DLNUR([Indu=Fin])	-1.351796	3.902319	557.000	-.346	.729	-9.016857	6.313265
DLNUR([Indu=Manu])	2.853102	3.902319	557.000	.731	.465	-4.811958	10.518163
DLNUR([Indu=Other])	1.445225	3.902319	557.000	.370	.711	-6.219835	9.110286
DLNUR([Indu=Rest])	1.722386	3.902319	557.000	.441	.659	-5.942675	9.387446
DLNUR([Indu=sale])	3.249096	3.902319	557.000	.833	.405	-4.415964	10.914157
DLNUR([Indu=Serv])	1.843977	3.902319	557.000	.473	.637	-5.821084	9.509037
DLNUR([Indu=Trans])	0[a]	0	.	.	.	.	.
DLNSP([Indu=bak])	-1.964342	2.643711	557.000	-.743	.458	-7.157204	3.228520
DLNSP([Indu=cons])	1.611224	2.267304	557.000	.711	.478	-2.842287	6.064735
DLNSP([Indu=Fin])	-.260064	2.267304	557.000	-.115	.909	-4.713575	4.193447
DLNSP([Indu=Manu])	-.948154	2.267304	557.000	-.418	.676	-5.401664	3.505357
DLNSP([Indu=Other])	.007329	2.267304	557.000	.003	.997	-4.446182	4.460840
DLNSP([Indu=Rlest])	-2.293277	2.267304	557.000	-1.011	.312	-6.746788	2.160234
DLNSP([Indu=sale])	-3.119532	2.267304	557.000	-1.376	.169	-7.573043	1.333979
DLNSP([Indu=Serv])	.549357	2.267304	557.000	.242	.809	-3.904154	5.002868
DLNSP([Indu=Trans])	0[a]	0	.	.	.	.	.
DLNExch([Indu=bak])	2.801156	4.463425	557.000	.628	.531	-5.966047	11.568360
DLNExch([Indu=cons])	-6.891845	3.713659	557.000	-1.856	.064	-14.186332	.402643
DLNExch([Indu=Fin])	-.148564	3.713659	557.000	-.040	.968	-7.443052	7.145924
DLNExch([Indu=Manu])	-4.562901	3.713659	557.000	-1.229	.220	-11.857389	2.731586
DLNExch([Indu=Other])	-4.317757	3.713659	557.000	-1.163	.245	-11.612245	2.976731
DLNExch([Indu=Rest])	-.233914	3.713659	557.000	-.063	.950	-7.528402	7.060573
DLNExch([Indu=sale])	-5.132773	3.713659	557.000	-1.382	.167	-12.427261	2.161715
DLNExch([Indu=Serv])	-4.970618	3.713659	557.000	-1.338	.181	-12.265106	2.323870
DLNExch([Indu=Trans])	0[a]	0	.	.	.	.	.

Table 9 Estimated Fixed Effect – Denmark

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.503330	.181991	174.000	-2.766	.006	-.862525	-.144136
[Indo=bak]	-.097960	.257374	174.000	-.381	.704	-.605938	.410017
[Indo=fin]	-.207043	.257374	174.000	-.804	.422	-.715020	.300935
[Indo=manu]	.196184	.257374	174.000	.762	.447	-.311793	.704161
[Indo=other]	-.249244	.257374	174.000	-.968	.334	-.757222	.258733
[Indo=rest]	-.640896	.497952	174.000	-1.287	.200	-1.623700	.341908
[Indo=sale]	.487852	.257374	174.000	1.895	.060	-.020125	.995830
[Indo=serv]	.971292	.257374	174.000	3.774	.000	.463315	1.479270
[Indo=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.624133	.252899	174.000	2.468	.015	.124988	1.123277
DLNCPI	-51.6366	34.220888	174.000	-1.509	.133	-119.178114	15.904835
DLNSP	-6.923141	3.351422	174.000	-2.066	.040	-13.537814	-.308469
DLNExch	-3.390434	4.615973	174.000	-.735	.464	-12.500940	5.720072
DLNSpread([Indo=bak])	-.541400	.357653	174.000	-1.514	.132	-1.247297	.164497
DLNSpread([Indo=fin])	-.422172	.357653	174	-1.180	.239	-1.128069	.283724
DLNSpread([Indo=manu])	.056357	.357653	174	.158	.875	-.649540	.762254
DLNSpread([Indo=other])	.362687	.357653	174.000	1.014	.312	-.343210	1.068584
DLNSpread([Indo=rest])	-.378847	.426075	174.000	-.889	.375	-1.219788	.462093
DLNSpread([Indo=sale])	-.153991	.357653	174.000	-.431	.667	-.859888	.551906
DLNSpread([Indo=serv])	.065417	.357653	174.000	.183	.855	-.640480	.771314
DLNSpread([Indo=trans])	0[a]	0	.	.	.	.	.
DLNCPI([Indo=bak])	37.021753	48.395645	174.000	.765	.445	-58.496316	132.539822
DLNCPI([Indo=fin])	25.289176	48.395645	174.000	.523	.602	-70.228894	120.807245
DLNCPI([Indo=manu])	.767861	48.395645	174.000	.016	.987	-94.750209	96.285930
DLNCPI([Indo=other])	-20.6400	48.395645	174.000	-.426	.670	-116.158027	74.878112
DLNCPI([Indo=rest])	21.761128	77.832119	174.000	.280	.780	-131.855460	175.377716
DLNCPI([Indo=sale])	17.788280	48.395645	174.000	.368	.714	-77.729790	113.306349
DLNCPI([Indo=serv])	.957540	48.395645	174.000	.020	.984	-94.560530	96.475609
DLNCPI([Indo=trans])	0[a]	0	.	.	.	.	.
DLNSP([Indo=bak])	4.510275	4.739626	174.000	.952	.343	-4.844284	13.864834
DLNSP([Indo=fin])	4.202952	4.739626	174.000	.887	.376	-5.151607	13.557511
DLNSP([Indo=manu])	3.081591	4.739626	174.000	.650	.516	-6.272969	12.436150
DLNSP([Indo=other])	5.399417	4.739626	174.000	1.139	.256	-3.955143	14.753976
DLNSP([Indo=rest])	6.919095	8.295173	174.000	.834	.405	-9.453018	23.291207
DLNSP([Indo=sale])	4.179488	4.739626	174.000	.882	.379	-5.175071	13.534047
DLNSP([Indo=serv])	3.043010	4.739626	174.000	.642	.522	-6.311549	12.397569
DLNSP([Indo=trans])	0[a]	0	.	.	.	.	.
DLNExch([Indo=bak])	2.512688	6.527971	174.000	.385	.701	-10.371513	15.396889
DLNExch([Indo=fin])	1.651570	6.527971	174.000	.253	.801	-11.232631	14.535771
DLNExch([Indo=manu])	-2.915613	6.527971	174.000	-.447	.656	-15.799814	9.968588
DLNExch([Indo=other])	-3.780793	6.527971	174.000	-.579	.563	-16.664994	9.103408
DLNExch([Indo=rest])	.121653	8.949162	174.000	.014	.989	-17.541232	17.784538
DLNExch([Indo=sale])	-1.114670	6.527971	174.000	-.171	.865	-13.998871	11.769531
DLNExch([Indo=serv])	-1.692359	6.527971	174.000	-.259	.796	-14.576560	11.191842
DLNExch([Indo=trans])	0[a]	0	.	.	.	.	.

Table 10 Estimates Fixed Effect – Norway

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-1.627925	.065534	457.000	-24.841	.000	-1.756710	-1.499140
[Indu=bak]	-.048248	.142760	457.000	-.338	.736	-.328795	.232299
[Indu=cons]	.826650	.092679	457.000	8.919	.000	.644520	1.008780
[Indu=fin]	-.159958	.092679	457.000	-1.726	.085	-.342088	.022172
[Indu=manu]	.923787	.092679	457.000	9.968	.000	.741657	1.105917
[Indu=rest]	.051170	.092679	457.000	.552	.581	-.130960	.233300
[Indu=sale]	1.546269	.092679	457.000	16.684	.000	1.364139	1.728399
[Indu=serv]	1.560622	.092679	457.000	16.839	.000	1.378492	1.742752
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.164219	.353845	457.000	.464	.643	-.531146	.859583
DLNSP	-.182347	.561475	457.000	-.325	.746	-1.285740	.921047
DLNSpread([Indu=bak])	-.866150	.527155	457.000	-1.643	.101	-1.902098	.169798
DLNSpread([Indu=cons])	.334626	.500412	457.000	.669	.504	-.648768	1.318020
DLNSpread([Indu=fin])	.376858	.500412	457.000	.753	.452	-.606535	1.360252
DLNSpread([Indu=manu])	.780917	.500412	457.000	1.561	.119	-.202477	1.764310
DLNSpread([Indu=rest])	.310690	.500412	457.000	.621	.535	-.672704	1.294083
DLNSpread([Indu=sale])	.285545	.500412	457.000	.571	.569	-.697848	1.268939
DLNSpread([Indu=serv])	.348137	.500412	457.000	.696	.487	-.635257	1.331531
DLNSpread([Indu=trans])	0[a]	0	.	.	.	.	.
DLNSP([Indu=bak])	1.109816	1.139068	457.000	.974	.330	-1.128645	3.348276
DLNSP([Indu=cons])	-.411251	.794046	457.000	-.518	.605	-1.971685	1.149183
DLNSP([Indu=fin])	.015279	.794046	457.000	.019	.985	-1.545155	1.575714
DLNSP([Indu=manu])	-1.193739	.794046	457.000	-1.503	.133	-2.754173	.366695
DLNSP([Indu=rest])	-.059145	.794046	457.000	-.074	.941	-1.619579	1.501289
DLNSP([Indu=sale])	-.733985	.794046	457.000	-.924	.356	-2.294420	.826449
DLNSP([Indu=serv])	-.760818	.794046	457.000	-.958	.338	-2.321253	.799616
DLNSP([Indu=trans])	0[a]	0	.	.	.	.	.

Table 11 Estimated Fixed Effects – Finland

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.310691	.051440	340.000	-6.040	.000	-.411871	-.209511
[Indu=agri]	.555447	.072746	340.000	7.635	.000	.412358	.698537
[Indu=bak]	-1.101627	.072746	340.000	-15.143	.000	-1.244717	-.958537
[Indu=cons]	.235195	.072746	340.000	3.233	.001	.092105	.378285
[Indu=fin]	-1.468258	.072746	340.000	-20.183	.000	-1.611348	-1.325168
[Indu=manu]	.314885	.072746	340.000	4.329	.000	.171796	.457975
[Indu=other]	.230543	.072746	340.000	3.169	.002	.087453	.373633
[Indu=rest]	-1.254682	.072746	340.000	-17.247	.000	-1.397771	-1.111592
[Indu=sale]	.294274	.072746	340.000	4.045	.000	.151184	.437364
[Indu=serv]	1.259504	.072746	340.000	17.314	.000	1.116414	1.402594
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.231824	.106600	340.000	2.175	.030	.022146	.441503
DLNSP	-1.247784	1.455780	340.000	-.857	.392	-4.111254	1.615686
DLNSpread([Indu=agri])	.201892	.150755	340.000	1.339	.181	-.094638	.498423
DLNSpread([Indu=bak])	-.173400	.150755	340.000	-1.150	.251	-.469931	.123130
DLNSpread([Indu=cons])	-.039882	.150755	340.000	-.265	.792	-.336412	.256648
DLNSpread([Indu=fin])	-.120961	.150755	340.000	-.802	.423	-.417491	.175570
DLNSpread([Indu=manu])	-.031535	.150755	340.000	-.209	.834	-.328066	.264995
DLNSpread([Indu=other])	.042631	.150755	340.000	.283	.778	-.253899	.339161
DLNSpread([Indu=rest])	.016438	.150755	340.000	.109	.913	-.280093	.312968
DLNSpread([Indu=sale])	-.050730	.150755	340.000	-.337	.737	-.347260	.245800
DLNSpread([Indu=serv])	-.109068	.150755	340.000	-.723	.470	-.405598	.187463
DLNSpread([Indu=trans])	0[a]	0	.	.	.	.	.
DLNSP([Indu=agri])	1.013942	2.058784	340.000	.492	.623	-3.035616	5.063500
DLNSP([Indu=bak])	-.402564	2.058784	340.000	-.196	.845	-4.452123	3.646994
DLNSP([Indu=cons])	-.816321	2.058784	340.000	-.397	.692	-4.865879	3.233237
DLNSP([Indu=fin])	-2.426290	2.058784	340.000	-1.179	.239	-6.475848	1.623268
DLNSP([Indu=manu])	-.699496	2.058784	340.000	-.340	.734	-4.749054	3.350062
DLNSP([Indu=other])	-1.447728	2.058784	340.000	-.703	.482	-5.497286	2.601831
DLNSP([Indu=rest])	1.487246	2.058784	340.000	.722	.471	-2.562312	5.536804
DLNSP([Indu=sale])	-1.920604	2.058784	340.000	-.933	.352	-5.970162	2.128954
DLNSP([Indu=serv])	-.882532	2.058784	340.000	-.429	.668	-4.932090	3.167026
DLNSP([Indu=trans])	0[a]	0	.	.	.	.	.

Table 12Estimated Fixed Effects—UK

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.078239	.082824	589.000	.945	.345	-.084428	.240906
[Indu=agri]	-.239358	.117131	589.000	-2.044	.041	-.469404	-.009313
[Indu=bak]	-1.447699	.123197	589.000	-11.751	.000	-1.689658	-1.205739
[Indu=cons]	1.091526	.117131	589.000	9.319	.000	.861481	1.321572
[Indu=fin]	-.863978	.117131	589.000	-7.376	.000	-1.094024	-.633932
[Indu=manu]	-.411166	.117131	589.000	-3.510	.000	-.641212	-.181120
[Indu=Others]	.962123	.117131	589.000	8.214	.000	.732078	1.192169
[Indu=rest]	-1.165930	.117131	589.000	-9.954	.000	-1.395975	-.935884
[Indu=sale]	-.030536	.117131	589.000	-.261	.794	-.260582	.199509
[Indu=serv]	1.061570	.117131	589.000	9.063	.000	.831524	1.291615
[Indu=trans]	0[a]	0	.	.	.	.	.
DLNSpread	.017890	.215664	589.000	.083	.934	-.405675	.441454
DLNUR	2.867313	3.533925	589.000	.811	.417	-4.073314	9.807940
DLNCPI	-12.7750	11.946984	589.000	-1.069	.285	-36.238860	10.688886
DLNExch	-3.539591	3.295851	589.000	-1.074	.283	-10.012641	2.933459
DLNSpread([Indu=agri])	.265194	.304995	589.000	.870	.385	-.333817	.864205
DLNSpread([Indu=bak])	.231034	.305699	589.000	.756	.450	-.369360	.831427
DLNSpread([Indu=cons])	-.033635	.304995	589.000	-.110	.912	-.632646	.565376
DLNSpread([Indu=fin])	.177074	.304995	589.000	.581	.562	-.421937	.776085
DLNSpread([Indu=manu])	.170461	.304995	589.000	.559	.576	-.428550	.769472
DLNSpread([Indu=Other])	.686935	.304995	589.000	2.252	.025	.087924	1.285946
DLNSpread([Indu=rest])	.145560	.304995	589.000	.477	.633	-.453451	.744571
DLNSpread([Indu=sale)	.166190	.304995	589.000	.545	.586	-.432820	.765201
DLNSpread([Indu=serv])	.618842	.304995	589.000	2.029	.043	.019831	1.217853
DLNSpread([Indu=trans])	0[a]	0	.	.	.	.	.
DLNUR([Indu=agri])	3.960099	4.997724	589.000	.792	.428	-5.855430	13.775628
DLNUR([Indu=bak])	-3.574938	5.088018	589.000	-.703	.483	-13.567804	6.417929
DLNUR([Indu=cons])	3.650076	4.997724	589.000	.730	.465	-6.165452	13.465605
DLNUR([Indu=fin])	-1.254476	4.997724	589.000	-.251	.802	-11.070004	8.561053
DLNUR([Indu=manu])	2.416338	4.997724	589.000	.483	.629	-7.399191	12.231866
DLNUR([Indu=Other])	5.662475	4.997724	589.000	1.133	.258	-4.153054	15.478003
DLNUR([Indu=rest])	.370032	4.997724	589.000	.074	.941	-9.445496	10.185561
DLNUR([Indu=sale])	2.132207	4.997724	589.000	.427	.670	-7.683322	11.947735
DLNUR([Indu=serv])	4.453872	4.997724	589.000	.891	.373	-5.361656	14.269401
DLNUR([Indu=trans])	0[a]	0	.	.	.	.	.
DLNCPI([Indu=agri])	-14.0607	16.895586	589.000	-.832	.406	-47.243675	19.122180
DLNCPI([Indu=bak])	14.050717	28.545577	589.000	.492	.623	-42.012790	70.114224
DLNCPI([Indu=cons])	-7.048786	16.895586	589.000	-.417	.677	-40.231713	26.134142
DLNCPI([Indu=fin)	8.805881	16.895586	589.000	.521	.602	-24.377046	41.988809
DLNCPI([Indu=manu])	-5.698778	16.895586	589.000	-.337	.736	-38.881705	27.484150
DLNCPI([Indu=Others])	-10.5995	16.895586	589.000	-.627	.531	-43.782432	22.583423
DLNCPI([Indu=rest])	1.182878	16.895586	589.000	.070	.944	-32.000049	34.365806
DLNCPI([Indu=sale])	-2.362609	16.895586	589.000	-.140	.889	-35.545537	30.820318
DLNCPI([Indu=serv])	-1.899255	16.895586	589.000	-.112	.911	-35.082183	31.283672
DLNCPI([Indu=trans])	0[a]	0	.	.	.	.	.
DLNExch([Indu=agri])	-5.052943	4.661037	589.000	-1.084	.279	-14.207218	4.101332
DLNExch([Indu=bak])	.224201	4.710438	589.000	.048	.962	-9.027099	9.475501
DLNExch([Indu=cons])	2.105493	4.661037	589.000	.452	.652	-7.048782	11.259768
DLNExch([Indu=fin])	-1.304550	4.661037	589.000	-.280	.780	-10.458825	7.849725
DLNExch([Indu=manu])	-1.493822	4.661037	589.000	-.320	.749	-10.648097	7.660453
DLNExch([Indu=Others])	-10.1258	4.661037	589.000	-2.172	.030	-19.280062	-.971512
DLNExch([Indu=rest])	.029857	4.661037	589.000	.006	.995	-9.124418	9.184132
DLNExch([Indu=sale])	-.452799	4.661037	589.000	-.097	.923	-9.607074	8.701476
DLNExch([Indu=serv])	-7.144353	4.661037	589.000	-1.533	.126	-16.298628	2.009922
DLNExch([Indu=trans])	0[a]	0	.	.	.	.	.

Table 13 Estimates of Fixed Effects – Germany

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-1.482991	.056631	141.000	-26.187	.000	-1.594945	-1.371036
[Indu=bak]	-.066058	.080088	141.000	-.825	.411	-.224386	.092269
[Indu=fin]	.199228	.080088	141	2.488	.014	.040900	.357556
[Indu=rest]	0[a]	0	.	.	.	.	.
DLNSpread	2.126382	.255025	141	8.338	.000	1.622215	2.630549
DLNUR	8.926069	1.951141	141.000	4.575	.000	5.068797	12.783341
DLNCPI	-38.6365	13.534161	141.000	-2.855	.005	-65.392620	-11.880400
DLNSP	-5.541399	1.228812	141.000	-4.510	.000	-7.970676	-3.112123
DLNIP	-18.0943	9.784316	141	-1.849	.067	-37.437211	1.248636
DLNSpread([Indu=bak])	-1.029067	.360660	141.000	-2.853	.005	-1.742067	-.316067
DLNSpread([Indu=fin])	-.772959	.360660	141.000	-2.143	.034	-1.485959	-.059959
DLNSpread([Indu=rest])	0[a]	0	.	.	.	.	.
DLNUR([Indu=bak])	-3.693767	2.759330	141	-1.339	.183	-9.148773	1.761239
DLNUR([Indu=fin])	-3.218973	2.759330	141.000	-1.167	.245	-8.673979	2.236033
DLNUR([Indu=rest)	0[a]	0	.	.	.	.	.
DLNCPI([Indu=bak])	16.432790	19.140194	141.000	.859	.392	-21.406063	54.271643
DLNCPI([Indu=fin])	9.656188	19.140194	141.000	.504	.615	-28.182665	47.495041
DLNCPI([Indu=rest])	0[a]	0	.	.	.	.	.
DLNSP([Indu=bak])	1.817678	1.737802	141.000	1.046	.297	-1.617837	5.253194
DLNSP([Indu=fin])	1.242867	1.737802	141.000	.715	.476	-2.192648	4.678383
DLNSP([Indu=rest])	0[a]	0	.	.	.	.	.
DLNIP([Indu=bak])	4.609888	13.837113	141.000	.333	.740	-22.745136	31.964913
DLNIP([Indu=fin])	6.223274	13.837113	141	.450	.654	-21.131751	33.578298
DLNIP([Indu=rest])	0[a]	0	.	.	.	.	.

Table 14 Estimates of Fixed Effects-- US