The Construction of an Investor Sentiment Index for Sweden and its Impact on the Stock Market

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Abstract

Investor sentiment is an important research object in behavioral finance, and its analysis has been one of the hot topics in stock market research recently. As an abstract concept, investor sentiment needs to be visualized by the construction of the investor sentiment index. In 2006, Baker and Wurgler proposed the Baker & Wurgler (BW) index, which can reflect investor sentiment in the American market. Based on the fundamental investor sentiment index BW, we develop and propose a new index *RSent* adapted to the Swedish market by principal component analysis. The new index *RSent* involves six variables (economic sentiment index, consumer confidence index, turnover, IPO number, IPO return, and equity-to-debt ratio) and constrains it by the macroeconomic environment’s impact. Furthermore, we explored the impact of this index on the Swedish stock market performance as represented by OMXS 30 and OMXS PI. We find that this investor sentiment has a positive impact on the Swedish stock market performance.

Key Words: Investor sentiment, principal component analysis, Swedish stock market

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1. Introduction

In the mid-eighteenth century, Adam Smith first proposed the rational investor theory, that is, costs and benefits will be measured and compared before people decide to buy or sell. In the financial markets, investors are influenced by investor sentiment, so cannot always remain rational when they participate in various transactions. Investor sentiment, defined broadly, is a belief about future cash flows and investment risks not justified by the facts at hand (Baker & Wurgler, 2007). This belief is a subjective assessment of the investor, it depends on investment preferences, investment experience, and social backgrounds. Hence, different investors may have different investor sentiments. Several studies have shown that investor sentiment can have an impact on financial markets and can explain some phenomena in stock prices. For instance, DeLong et al. (1990) found that investor sentiment may make market prices diverge significantly from fundamental values and lead to many financial anomalies. Chang and Shu (2015) found that investor sentiment can adequately interpret high volatility, bubble and crash formation in the financial market.

Here, we choose the Swedish stock market as the research object. On the one hand, the Swedish stock market is an important securities exchange market of the Nordic countries. However, there are few related studies on investor sentiment index construction for Sweden. On the other hand, the Swedish stock market has a relatively low proportion of household investors (12% in 2021 from Statista, 2021) compared to other main markets represented by the USA (37.7% in 2021 from SIFMA), China (31.4% in 2019 from BOC Research, 2021) and France (24.3% in 2021 from Statista, 2023). Retail investors are more susceptible to investor sentiment, and their systematic activities will affect the returns of stocks (Kumar & Lee, 2006). Therefore, whether investor sentiment has a noticeable impact on the overall Swedish stock market and how investor sentiment affects the market, becomes our motivation for this research.

Investor sentiment is an abstract concept, so constructing a suitable investor sentiment index is essential to measure and qualify it. A suitable sentiment index should be intuitive, and it should have a reasonably high correlation with investor sentiment. The purpose of our thesis is to investigate how to construct a valid investor sentiment index and whether this index has an impact on the market. Based on six variables in the Swedish market (economic sentiment index, consumer confidence index, turnover, IPO number, IPO return, and equity-to-debt ratio), we construct a new investor sentiment index called *RSent*. There are three basic steps in the construction process. Firstly, explore the relationship between lead and lag in the time of variables reflecting investor sentiment. And choose whether to use the variable's lead data or the lag data for index construction. Secondly, use the selected variables to construct the primary sentiment index called *ESent* by the principal component analysis. Finally, in order to focus on the investors themselves, control the influence of macroeconomics in the constructed sentiment index *ESent*. Then construct a new sentiment index called *RSent* by using principal component analysis again.

After the construction, we analyze the relationship between investor sentiment and the Swedish stock market performance. In this process, we use the constructed index *RSent* to measure investor sentiment, and the OMXS 30 and OMXS PI to represent the Swedish stock market performance.

The rest of this thesis is organized as follows. Section 2 introduces related literature on investor sentiment. Section 3 describes our data. Section 4 constructs the investor sentiment index and analyzes its impact on the Swedish stock market. Section 5 concludes.

2. Related Literature

2.1 Sentiment Indicators

There has been much research related to investor sentiment indicators. Sentiment indicators, depending on their complexity, can be divided into single variable indicators and composite variable indicators.

2.1.1 Single Variable Indicators

Indicators that can reflect investor sentiment without any processing are single variable indicators. Among single indicators, several of them can directly reflect investor sentiment, such as the economic sentiment index (ESI) and consumer confidence index (CCI) (Cibulskienė & Grigaliūnienė, 2010). Moreover, the America Association of Individual Investors collects sentiment data through questionnaires, and Investors Intelligence publishes the sentiment index weekly (Brown & Cliff, 2004; Fisher & Statman, 2000). These indicators can reflect changes in investor sentiment subjectively. However, Fisher and Statman (2000) found that individual investors are wiser in their investment actions than in their sentiments, which suggests that these indicators cannot reflect investor sentiment completely comprehensively and reliably. Hence, these indicators cannot independently reflect the real sentiment of investors in the trades.

In addition, more indicators that reflect investor sentiment indirectly are focused on by some researchers, including the closed-end fund discounts (CEFD) (Lee et al. 1991), the odd-lot sales to purchase rate (ODDLOT) (Brown & Cliff, 2004), the market liquidity (Baker & Stein, 2004) and so on. These types of indicators are objective, they do not start from the subjective feelings of market participants. However, they reflect the change in investor sentiment through the objective performance of the market. These kinds of market performance do not depend only on investor sentiment, there are numbers of other factors at play as well. Thus, only using these indicators that reflect sentiment indirectly as the measures is not absolutely reasonable, either.

2.1.2 Composite Variable Indicators

A composite variable comprises two or more variables or measures that are highly related to one another conceptually or statistically.

Many variables reflect investor sentiment, but each sentiment variable is likely to include a sentiment component as well as idiosyncratic, non-sentiment-related components (Baker & Wurgler, 2006). In order to fix this problem, Baker and Wurgler (2006) used six variables, discounts in closed-end fund, trading volume, the number of IPO, the average first-day return, the share of equity issues in total equity and debt issues, and the dividend premium to construct a sentiment index called Baker & Wurgler (BW) index.

However, we find that this index lacks a component that can reflect investor sentiment directly. Thus, compared with the BW index, we add the economic sentiment index (*ESI*) and the consumer confidence index (*CCI*), which reflect investor sentiment directly in the Swedish market to make it more comprehensive. Furthermore, we use monthly data instead of yearly data to reflect the change in investor sentiment more exactly. Like the approach used by Baker and Wurgler (2006), we also use principal component analysis (PCA) to construct a new index of investor sentiment for Sweden.

2.2 The Relationship between Investor Sentiment and Stock Market

There has been much research on the impact of investor sentiment on equity markets. Most of these studies focused on the US market. For example, Brown and Cliff (2004) found limited evidence to support that market sentiment has a predictive ability for near-term future stock returns in the US market. Gebka (2014) discovered that there are connections, both linear and nonlinear, between sentiment and future stock returns. There are also studies based on the Chinese and German markets. Sun and Wang (2004) found that changes in investor sentiment not only significantly affect Chinese stock returns, but also significantly reverse-correct Chinese stock return volatility. Lee (2019) detected that investor sentiment is highly correlated with stock returns and validated the efficacy of multiple financial variables in forecasting stock returns. Finter et al. (2012) identified investor sentiment exhibits sensitivity to stocks characterized by limited arbitrage opportunities and challenging valuation in the German stock market.

As can be seen, there is no conclusive evidence regarding the impact of investor sentiment on the stock market. Possibly, the impact of investor sentiment may vary across countries and regions, and the use of different measures of investor sentiment can also yield uncertain results. As for the study on the Swedish stock market, most relevant paper is the study on the Scandinavian stock market (Cibulskienė &

Grigaliūnienė, 2010). This paper shows that the consumer confidence index can predict value stock portfolio returns for one and six months for the Swedish stock market.

Nevertheless, it lacks research to use the composite indicator to investigate the Swedish stock market. Therefore, our paper differs from these previous papers, we focus on the Swedish stock market. We construct a new composite indicator as an investor sentiment index based on the BW index instead of using a few specific single indicators to reflect sentiment better.

3. Data

3.1 Variables Selection for Investor Sentiment

The selection of factors should reflect the different information of investors from the subjective and objective dimensions representatively to express the trend of their investment sentiment. Considering the realities of the Swedish stock market and data availability, our variables' selection mainly refers to the construction of the BW index. Furthermore, we modify it with other research in the investor sentiment index. The following six variables, Economic Sentiment Index, Consumer Confidence Index, Turnover, IPO Number, IPO Return, and Equity-to-Debt Ratio (inverted debt-to-equity ratio) are selected to construct the investor sentiment index for the Swedish stock market. They are monthly data from January 2014 to December 2022, with 108 observations for each variable. Data sources are from Bloomberg.

3.1.1 Economic Sentiment Index (*ESI*)

The economic sentiment index measures the strength of confidence in the economic environment and generally covers various industries, including industry, services, consumers, construction, and retail trade. *ESI* aims to monitor and forecast the business cycle of a country or region and tends to show the market participants' prospects for the future. When this index grows, it suggests that the market is positive and has a high expectation for the economic prospect. Investors may have positive sentiment in this situation. Cibulskienė and Grigaliūnienė (2010) used the economic sentiment index to investigate the Scandinavian stock market.

3.1.2 Consumer Confidence Index (*CCI*)

The consumer confidence index (*CCI*) was first set up by George Katona in the late 1940s, which shows the consumption level and indicates economic growth. It can reflect comprehensively and quantify the consumers' assessments of the current economic situation. The index takes into account consumers' subjective performance in terms of household financial prospects, income levels and consumption. Moreover, it is a leading indicator that may forecast the economic trend and consumption direction.

The *CCI* can be used as an overall feedback indicator for investor sentiment based on the outlook of their financial situation. (Qiu & Welch, 2006). Bandopadhyaya and Jones (2006) used the consumer confidence index to investigate equity markets. *CCI* is widely used as the evaluation of how economic prospects and expected financial situations influence households' decisions. When the consumer confidence index increases or its growth rate maintains a certain level, it illustrates a better-than-expected economic environment trend, and the future is more conducive to investor confidence in investing. Investors therefore, may tend to show more positive sentiment in this environment. Here we choose the monthly growth rate of the *CCI* index to construct the investor sentiment index.

3.1.3 Turnover (*TURN*)

Turnover represents the frequency with which the share changes hands in the stock market during a given period. It can be calculated as the total trading volume of the outstanding shares. This variable shows the liquidity and activity of the market. When the turnover maintains a higher number, that means the investors in the market change their positions more frequently. The investors show a willing attitude in trading stocks, leading to more positive sentiment.

Moreover, many markets were characterized by a strong link between trading volume and market liquidity, and turnover could be representative of trading volume (Baker & Stein, 2004). Also, there may be two-way effects between turnover and market activity. Higher overall market activity mobilizes the emotions of some investors who were initially unwilling to trade and join in the transaction, a performance of herd behavior. In turn, new investors continue to contribute to a more active market performance. Thus, the performance of market activity can reflect investor sentiment. We choose the turnover for the Swedish market, and the data processing takes the logarithm of *TURN* to weaken the potential effect of the extremely large number in trading volume.

3.1.4 IPO Number (*NIPO*) and IPO Return *(RIPO)*

IPO activity is strongly correlated with investment conditions. It namely creates the underlying stocks as target assets that investors can directly choose from in the market. Data relating to IPO activity is closely watched by investors and discreetly referenced when they choose to invest. Thereby affecting investor behavior and sentiment. In our thesis, we choose the IPO number and IPO return as the two main indicators to represent the influence of the IPO activity on investor sentiment.

IPO number is the volume of new shares appearing on the market. If more new stocks appear quickly, it gives more choices to investors for new investment targets. In contrast to a market with fewer stocks, investors are more susceptible to the more targets available: More stocks, different types of stocks, and different business characteristics of listed companies. These allow investors to construct their portfolios according to their preferences and develop more favorable and personal investment choices. For example, some household investors may tend to hold many different stocks with each low position, and some may prefer to invest in a specific field of companies…investors may act differently with more options available. While the IPO number, which represents newly added stocks, gives these investors more choices and lets them invest based on their own preferences, thus promoting their willingness to invest.

IPO return even more directly influences investor sentiment, with higher returns simply motivating investors' wishes to earn more profit. A good return will make investors more optimistic and willing to enter the stock market. Therefore, the correlation between IPO return with investor sentiment should be positive. Moreover, Loughran and Ritter (1995) stated that because the IPO return will bring investors a higher willingness to invest, companies tend to use this positive attitude to arrange their IPOs schedule.

In addition, many other studies have used the IPO number and the IPO return to construct a sentiment index. Finter et al. (2012) and Baker and Wurgler (2006) used IPO volume and IPO First-Day return as indicators in constructing the investor sentiment index, similar evidence from Brown and Cliff (2004) and Ljungqvist and William (2002). Hence, we pick the monthly IPO number of Sweden (including IPO-owned companies registered in Sweden) and the monthly IPO return of Sweden. Here, IPO return means the yield on the first day of issuance.

3.1.5 Equity-to-Debt Ratio (*E/D-Ratio*)

Baker and Wurgler (2000) found that managers prefer to issue equity and change their debt-to-equity ratio when investors buy the stock at an overvalued price. This overvalued and optimistic investor expectation of the market and stocks can be further explained by the high investor sentiment. More equity will issue instead of debt when investor sentiment is high. In other words, from the companies' perspective, they prefer to use equities as a source of financing to achieve excess capital gains. In a more negative market, the stocks' prices may not achieve the expected market valuation of the company. Therefore, companies would control their equity-to-debt ratio due to the undervaluing in this situation. In sum, the equity-to-debt ratio is like a link between corporate decisions and investors' valuing reflection. It could be chosen as an explanatory variable for investor behavior and sentiment in the market from the perspective of corporate decisions.

Note we use the inverted debt-to-equity ratio and name that equity-to-debt ratio (*E/D-Ratio*) to better research the positive correlation between the equity structure with the investor sentiment in the following construction.

Of the six sentiment variables above, *ESI* and *CCI* are sentiment variables that can reflect the investor sentiment directly and subjectively, and the *TURN*, *NIPO*, *RIPO*, and *E/D-Ratio* can reflect the investor sentiment indirectly and objectively. Theoretically, investor sentiment is expected to have a positive correlation with all variables.

The descriptive statistics result of these data is listed as the following ***Table 1***:

Table 1: Descriptive statistics result of *ESI*, *CCI*, *TURN*, *NIPO*, *RIPO*, and *E/D-Ratio*

Variable	Mean	STDV	Min.	Max.	Median.	Obs
Economic Sentiment Index (ESI_t)	-0.0008	0.0435	-0.3280	0.1657	-0.0004	108
Consumer Confidence Index (CCI_t)	-0.0047	0.03	-0.1312	0.0799	-0.0021	108
Turnover ($TURN_t$)	9.93	0.40	9.18	11.27	9.89	108
IPO Number ($NIPO_t$)	9.97	8.01	0	39	8	108
IPO Returns ($RIPO_t$)	0.15	0.63	-0.80	3.18	0.0031	108
Equity Debt Ratio ($E/D\text{-}Ratio_t$)	0.0042	0.0010	0.0024	0.0064	0.0038	108

Monthly data from January 2014 to December 2022 via Bloomberg. ESI_t and CCI_t are measured by the growth rate. Logarithmic form for $TURN_t$. $NIPO_t$ including IPO-owned companies registered in Sweden. $RIPO_t$ measures the yield on the first day of issuance, the unit is in percent. $E/D\text{-}Ratio_t$ is the inverted OMX debt-to-equity ratio. We use STATA for data processing.

4. Methodology and Result

4.1 Discussion on the lead and lag relationship between the variables

The lead or lag items from the six selected variables may have differences in the effect on investor sentiment. It is therefore necessary to consider the relationship between lead and lag before constructing the real investor sentiment index for the Swedish market. And it is important to consider which of the six variables should be selected as the lead variables to influence the index.

A common approach without lead and lag treatment may ignore the impact of some lead variables in influencing investor decisions and sentiment. In other words, at a certain point in time, investors will refer to these historical lead indicators to determine how well or poorly the market will move in the future and change their positions accordingly. For example, IPO return reflects investor sentiment ahead of the IPO number in the American stock market. Because managers will decide whether to proceed with an IPO by observing the previous IPO returns, and also investors will also consider whether they should enter the market based on the market's previous equity yields. (Benveniste et al. 2003; Lowry & Schwert, 2002)

For data treatment, we make the six variables for six groups. Each group contains two variables: one is the lead (like ESI_{t-1}), and one is the lag (like ESI_t). And lead each period variable by one unit month for principal component analysis (PCA). Firstly, we have the Kaiser-Meyer-Olkin (KMO) measure for the identity correlation matrix to justify whether this dataset is suitable for PCA. The result of the KMO test is 0.531, larger than 0.5. It indicates adequate sampling and the PCA approach is suitable here.

Then, we do PCA on twelve variables, thereby constructing an investor sentiment index *Sent* that concludes: ESI_t, ESI_{t-1}, CCI_t, CCI_{t-1}, $TURN_t$, $TURN_{t-1}$, $NIPO_t$, $NIPO_{t-1}$, $RIPO_t$, $RIPO_{t-1}$, $E/D\text{-}Ratio_t$, $E/D\text{-}Ratio_{t-1}$. The explained variance for each component is shown in ***Table 2*** below.

Table2: PCA result for of ESI_t, ESI_{t-1}, CCI_t, CCI_{t-1}, $TURN_t$, $TURN_{t-1}$, $NIPO_t$, $NIPO_{t-1}$, $RIPO_t$, $RIPO_{t-1}$, $E/D\text{-}Ratio_t$, $E/D\text{-}Ratio_{t-1}$.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.2350	0.8774	0.2696	0.2696
Comp2	2.3577	0.1993	0.1965	0.4661
Comp3	2.1584	0.7825	0.1799	0.6459
Comp4	1.3759	0.5394	0.1147	0.7606
Comp5	0.8365	0.1056	0.0697	0.8303
Comp6	0.7309	0.3363	0.0609	0.8912
Comp7	0.3946	0.0723	0.0329	0.9241
Comp8	0.3224	0.0787	0.0269	0.9509
Comp9	0.2436	0.0202	0.0203	0.9712
Comp10	0.2235	0.1409	0.0186	0.9899
Comp11	0.0826	0.0435	0.0069	0.9967
Comp12	0.0391	.	0.0033	1.0000

This table serves as the PCA result for the 12 variables, and we focus on the components with a cumulative explained variance greater than 85%, and they are the first six components.

To have a better interpretation of the model, we improve the BW index which only selects principal component 1. Instead, we use the principal component with a cumulative explained variance rate of more than 85% as the object for the following analysis. Multiple principal components have higher explanatory power relative to one principal component (Yi & Mao, 2009). Here, we choose the first six principal components, and the percentage of cumulative explained variance is 89.12%. And then, we get the eigenvectors matrix of six components from the PCA result, which is shown in ***Table 3***.

Table 3: Eigenvectors matrix of the components for lead and lag treatment

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
ESI_t	-0.0422	0.3022	0.3700	0.4495	-0.1132	0.2901
CCI_t	-0.1670	0.2696	0.2796	0.5470	0.0210	0.1039
$TURN_t$	0.3210	0.3285	-0.2757	-0.1084	0.3853	0.2245
$NIPO_t$	0.3185	0.2528	0.1979	0.0874	0.4928	-0.2833
$RIPO_t$	0.0058	0.5144	-0.3373	-0.1029	0.1858	0.1599
$E/D\text{-}Ratio_t$	0.4685	0.0788	-0.1164	0.1187	-0.4461	0.0589
ESI_{t-1}	0.0059	0.2818	0.3656	-0.4700	-0.2752	0.0952
CCI_{t-1}	-0.0898	0.2494	0.4077	-0.4714	-0.0450	0.0973
$TURN_{t-1}$	0.4007	-0.3347	0.2001	0.0370	0.1577	0.1286
$NIPO_{t-1}$	0.3433	0.0843	0.2799	0.0151	-0.0457	-0.6562
$RIPO_{t-1}$	0.1814	-0.3608	0.3309	-0.0911	0.3293	0.4694
$E/D\text{-}Ratio_{t-1}$	0.4763	0.0489	-0.1210	0.0403	-0.3856	0.2436

The table shows the eigenvectors of the 12 variables for six components.

Using the results of principal component analysis, we can now construct a score coefficient matrix for each variable that affects investor sentiment. Define the corresponding score coefficient of each variable factor as *isent*, and use the following formula (1) to calculate:

$$isent = \sum_{i=1}^{6} isent_i * \frac{r_i}{\sum_{i=1}^{6} r_i} \tag{1}$$

Among this, $isent_i$ is the eigenvector of the i^{th} principal component (in ***Table 3***), the r_i is the eigenvalue of the i^{th} principal component (in ***Table 2***). The score coefficient matrix is shown in ***Table 4***.

Table 4: Score coefficient matrix and the sum calculated *isent* for twelve variables

	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Sum
r_i/sum r_i	0.3025	0.2205	0.2018	0.1287	0.0782	0.0683	
ESI_t	-0.0128	0.0666	0.0747	0.0578	-0.0089	0.0198	0.1973
CCI_t	-0.0505	0.0594	0.0564	0.0704	0.0016	0.0071	0.1445
$TURN_t$	0.0971	0.0724	-0.0556	-0.0139	0.0301	0.0153	0.1454
$NIPO_t$	0.0963	0.0557	0.0399	0.0112	0.0385	-0.0194	0.2224
$RIPO_t$	0.0018	0.1134	-0.0681	-0.0132	0.0145	0.0109	0.0593
$E/D\text{-}Ratio_t$	0.1417	0.0174	-0.0235	0.0153	-0.0349	0.0040	0.1200
ESI_{t-1}	0.0018	0.0621	0.0738	-0.0605	-0.0215	0.0065	0.0622
CCI_{t-1}	-0.0272	0.0550	0.0823	-0.0606	-0.0035	0.0067	0.0526
$TURN_{t-1}$	0.1212	-0.0738	0.0404	0.0048	0.0123	0.0088	0.1137
$NIPO_{t-1}$	0.1038	0.0186	0.0565	0.0019	-0.0036	-0.0448	0.1324
$RIPO_{t-1}$	0.0549	-0.0795	0.0668	-0.0117	0.0258	0.0321	0.0882
$E/D\text{-}Ratio_{t-1}$	0.1441	0.0108	-0.0244	0.0052	-0.0302	0.0166	0.1221

In this table, the Sum column is the calculated *isent* for each variable. Each of the other columns is the multiplication of each $isent_i$ in the component with its r_i/sum r_i.

Then, we use the *isent* for twelve variables, multiply by the corresponding variables respectively and add them together to gain the *Sent*. The results are shown in the following equation (2):

$$Sent = 0.1973*ESI_t + 0.1445*CCI_t + 0.1454*TURN_t + 0.2224*NIPO_t + 0.0593*RIPO_t + 0.1200*E/D\text{-}Ratio_t + 0.0622*ESI_{t-1} + 0.0526*CCI_{t-1} + 0.1137*TURN_{t-1} + 0.1324*NIPO_{t-1} + 0.0882*RIPO_{t-1} + 0.1221*E/D\text{-}Ratio_{t-1} \quad (2)$$

Using the constructed *Sent*, we perform correlation tests for each variable with *Sent*. The result is shown in ***Table 5***. Twelve variables as sentiment indicators are all positively correlated with the *Sent*, consistent with our initial expectation.

As the final model should not have twelve variables that contain both lead and lag variables of the same group in it. It can cause over-fitting or misestimated of the model.

Thus, it is important to filter based on which of the lead and lag variables is more correlated with the *Sent* within the same group. By comparing the correlation coefficient between the lead and the lag of each group and *Sent*, a high correlation coefficient with *Sent* indicates that this variable responds better to the impact of investor sentiment than the other one.

Table 5: Correlation coefficient between the twelve variables and *Sent*

Variable	*Sent*	ESI_t	CCI_t	$TURN_t$	$NIPO_t$	$RIPO_t$	$E/D\text{-}Ratio_t$
ESI_t	0.2165	1					
CCI_t	0.0845	0.6633	1				
$TURN_t$	0.4033	-0.0783	-0.1669	1			
$NIPO_t$	0.9323	0.2351	0.1202	0.4339	1		
$RIPO_t$	0.0638	0.0461	0.0687	0.6889	0.1454	1	
$E/D\text{-}Ratio_t$	0.4274	0.0128	-0.186	0.4437	0.3293	0.1068	1
ESI_{t-1}	0.1998	0.2043	0.0953	0.0182	0.1447	0.1077	-0.0300
CCI_{t-1}	0.1514	0.2618	0.0862	-0.0751	0.1432	0.0551	-0.2119
$TURN_{t-1}$	0.4096	-0.0915	-0.2477	0.1592	0.2852	-0.5216	0.4283
$NIPO_{t-1}$	0.7902	0.1233	0.0165	0.1654	0.5175	-0.1153	0.4297
$RIPO_{t-1}$	0.1663	-0.0303	-0.1352	-0.1242	0.1194	-0.4993	0.0172
$E/D\text{-}Ratio_{t-1}$	0.3797	-0.0365	-0.2474	0.4854	0.3063	0.1102	0.8978

The blue block in the table represents the higher value in the group. For example, the correlation between $TURN_t$ with *Sent* is 0.4033. And the correlation between $TURN_{t-1}$ with *Sent* is 0.4096, which is higher than 0.4033. So, print the $TURN_{t-1}$ in blue, to represent choosing it as a variable in later construction rather than $TURN_t$.

As can be seen from the table, each ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$ are more highly correlated with *Sent* than the other variables. From the market's overall performance, the lead CCI_{t-1} has a significant impact on prospective investors (0.1514 compared to 0.0845 for CCI_t). While the difference between the two periods of *ESI* is not very obvious (0.2165 and 0.1998). The performance of *RIPO* and *NIPO* coefficients is also in line with market expectations: The impact of $RIPO_{t-1}$ is leading before $NIPO_t$. It shows the trend that when the market yield is high, corporate-level decisions will promote corporate listing and financing. Hence, the difference in the period between the two variables has effects on investor sentiment. At last, we choose ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$, these six variables to construct the investor sentiment index.

4.2 Construction of an investor sentiment index *ESent*

After completing the discussion of the relationship between lead and lag, we can obtain filtered six variables ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$. These variables have a relatively higher correlation and can be further used to construct the Swedish investor sentiment index *ESent*. In the following step, we use the PCA for these six selected variables and then get the result of explained variance for each component, which is shown in ***Table 6.***

Table 6: PCA result for ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.9924	0.5654	0.3321	0.3321
Comp2	1.4270	0.2591	0.2378	0.5699
Comp3	1.1679	0.4822	0.1946	0.7645
Comp4	0.6857	0.1484	0.1143	0.8788
Comp5	0.5372	0.3473	0.0895	0.9684
Comp6	0.1899	.	0.0316	1.0000

Following the principle of being able to explain at least 85% of the cumulative explained variance, we choose the first four components, which can explain 87.88% variance. Comparing the twelve variables' PCA result for total components cumulative variance explanation is 89.12%, new PCA result for the selected six variables still retains a good cumulative explanation rate.

Then we calculate the eigenvectors matrix and correlation coefficient matrix, which are shown in ***Table 7*** and ***Table 8***.

Table 7: Eigenvectors matrix of the six components constructed by ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
ESI_t	-0.0092	0.6418	-0.1466	0.7497	0.0464	-0.0483
$NIPO_t$	0.3722	0.4427	-0.323	-0.3936	-0.633	0.0747
$E/D\text{-}Ratio_t$	0.4347	-0.0564	-0.5871	-0.0784	0.601	0.3096
CCI_{t-1}	-0.1066	0.6133	0.3563	-0.4937	0.4779	-0.1159
$TURN_{t-1}$	0.6489	-0.1127	0.1743	0.0873	0.0742	-0.7230
$RIPO_{t-1}$	0.4899	0.0084	0.6101	0.1596	-0.0459	0.6001

Table 8: Correlation coefficient matrix for *ESent* with six variables

Variable	*ESent*	ESI_t	$NIPO_t$	$E/D\text{-}Ratio_t$	CCI_{t-1}	$NIPO_{t-1}$	$RIPO_{t-1}$
ESI_t	0.2123	1					
$NIPO_t$	0.9699	0.2351	1				
$E/D\text{-}Ratio_t$	0.3439	0.0128	0.3293	1			
CCI_{t-1}	0.1375	0.2618	0.1432	-0.2119	1		
$TURN_{t-1}$	0.4727	-0.0915	0.2852	0.4283	-0.1585	1	
$RIPO_{t-1}$	0.3500	-0.0303	0.1194	0.0172	0.0781	0.6816	1

In the first column, all six variables have correlation coefficients greater than 0 with the constructed *ESent*. Among them, $NIPO_t$ has the highest correlation coefficient, CCI_{t-1} is the smallest, and the correlation coefficients of the other four variables are relatively close.

The correlation coefficient table shows that *ESent* is positively correlated with all the sentiment variables. It also indicates that if the ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$ increase, they will have a positive impact on investor sentiment.

In conjunction with the descriptions given in the data selection: ESI_t and CCI_{t-1} represent future household financial prospects; $NIPO_t$ and $RIPO_{t-1}$ represent stock market IPO conditions; $E/D\text{-}Ratio_{t-1}$ represents company decision factors; and $TURN_{t-1}$ is market activity. It can be more simply understood here that: when future financial prospects, stock market IPO conditions, corporate decisions, and market activity are tending positive, investor sentiment, as represented by *ESent*, will also be optimistic and high. Because the correlation coefficients between these variables with *Esent* are positive. This aligns with the expectation when we construct the index during data selection.

Then we use equation (1) again:

$$isent = \sum_{i=1}^{6} isent_i * \frac{r_i}{\sum_{i=1}^{6} r_i} \quad (1)$$

to calculate the score coefficient matrix of each variable at this time, we can get ***Table 9***:

Table 9: Score coefficient matrix and the sum calculated *isent* for ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$

	Comp1	Comp2	Comp3	Comp4	Sum
r_i/sum r_i	0.3779	0.2706	0.2215	0.1300	
ESI_t	-0.0035	0.1737	-0.0325	0.0975	0.2352
$NIPO_t$	0.1406	0.1198	-0.0715	-0.0512	0.1377
$E/D\text{-}Ratio_t$	0.1643	-0.0153	-0.1300	-0.0102	0.0088
CCI_{t-1}	-0.0403	0.1660	0.0789	-0.0642	0.1404
$TURN_{t-1}$	0.2452	-0.0305	0.0386	0.0114	0.2646
$RIPO_{t-1}$	0.1851	0.0023	0.1351	0.0208	0.3433

Using the data in ***Table 6*** and ***Table 7***. In this table, the Sum column is each calculated *isent* for six variables. Each of the other columns is the multiplication of each $isent_i$ in the component with its r_i/sum r_i.

Using this score coefficient, we can get the model of *ESent* by equation (3):

$$ESent = 0.2352 * ESI_t + 0.1337 * NIPO_t + 0.0088 * E/D - Ratio_t + 0.1404 * CCI_{t-1} + 0.2646 * TURN_{t-1} + 0.3433 * RIPO_{t-1} \quad (3)$$

4.3 Construction of a sentiment index considering macroeconomic effects

Macroeconomic factors influence investor sentiment in a very natural way. When the external economic environment performs better, household investors' income is higher. Thus, they will have more spare money to invest and show a more optimistic attitude toward the market. This leads to an increase in investor sentiment. Matsusaka and Sbordone (1995), and Ludvigson (2004) found a positive correlation between investor confidence and macroeconomic cycles. Baker and Wurgler (2007) also found that investor sentiment varies with fluctuations in macroeconomic sentiment and removed the macro effects in the data processing. Finter et al. (2012) divided the PCA into groups (a) and (b) to control for the effects of macro factors, one is macro-adjusted and the other is not, and then compared these two PCA groups' results. Studies consider how to control the effects of macroeconomic factors in different ways for different purposes.

To further investigate whether the investor sentiment index retains its original characteristics and still has a positive correlation with each variable when some macroeconomic influences are removed. Here we mainly refer to the methodology of Yi and Mao (2009), regressing each variable of the index construction on macroeconomic indicators to obtain residuals to control the macro effects. Although macroeconomics will always affect the performance of the capital market, the purpose is to pay more attention to the investor's own behavior and sentiment. Moreover, to compare the result before and after controlling the macro effects.

We select the Swedish consumer price index (*CPI*), producer price index (*PPI*), industrial production (*IP*), and employment rate (*EM*) to represent the macroeconomic performance that needs to be controlled. They are all monthly data for Sweden, where the *CPI* data source is Bloomberg, the *PPI* and *EM* data source is Statistics Sweden, and the *IP* data source is OECD. *CPI* reflects the trend and extent of price changes in consumer goods and services purchased by residents to measure inflation and reflect the currency purchasing power. The *PPI* differs from the *CPI* in that *PPI* takes the perspective of the producer. The main objective of *PPI* is to measure the total cost of a basket of goods and services purchased by firms. And it influences future commodity price movements in the form of the final pass-through to consumers. *IP* is a more direct reflection of social production in terms of industrial output. *EM* uses the Labour Force Surveys from Statistics Sweden. Social employment is a macro-level reflection of the jobs available in the regional economy.

We process these macroeconomic data using the min-max normalization:

$$\boldsymbol{x_{normal}} = \frac{\boldsymbol{x_i - x_{min}}}{\boldsymbol{x_{max} - x_{min}}} \tag{4}$$

x_i denotes the original data, x_{max} denotes the maximum value of this set of data, x_{min} denotes the minimum value of this set of data, and x_{normal} denotes the proceed value after min-max normalization. The purpose of the normalization is: Regression without normalization can cause particularly large fluctuations in the residual series. There are differences between each macro data set: for example, in the *CPI* and *EM*, one is an index for measuring consumer prices and the other is for the employment rate in percentage. They are different in absolute value. Therefore, standardizing the data is more conducive to eliminating large fluctuating values in the residual series caused by changes in the absolute value of macroeconomics. This makes the residual series more stable. Thus, it facilitates the further construction of the sentiment index after controlling macroeconomic factors.

Then we run the regression of six variables ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$ on normalized *CPI*, *PPI*, *IP*, and *EM*, respectively, to calculate the residual series for six regressions. After getting the residual series: $rESI_t$, $rNIPO_t$, $rE/D\text{-}Ratio_t$, $rCCI_{t-1}$, $rTURN_{t-1}$, $rRIPO_{t-1}$, we process the PCA by using these six residual series, same as the steps above. The explained variance for each component result is shown in ***Table 10***.

Table 10: PCA result for the residual series: $rESI_t$, $rNIPO_t$, $rE/D\text{-}Ratio_t$, $rCCI_{t-1}$, $rTURN_{t-1}$, and $rRIPO_{t-1}$

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.8055	0.2103	0.3009	0.3009
Comp2	1.5952	0.6215	0.2659	0.5668
Comp3	0.9737	0.2528	0.1623	0.7291
Comp4	0.7209	0.0445	0.1202	0.8492
Comp5	0.6764	0.4482	0.1127	0.9620
Comp6	0.2283	.	0.0380	1.0000

We select the first five components to make the cumulative up to 96.2%, more than 85%. And then calculate the eigenvectors matrix, score coefficient matrix, and correlation coefficient matrix, which are shown in ***Table 11***, ***Table 12***, and ***Table 13***.

Table 11: Eigenvectors matrix of the five components constructed by $rESI_t$, $rNIPO_t$, $rE/D\text{-}Ratio_t$, $rCCI_{t-1}$, $rTURN_{t-1}$, and $rRIPO_{t-1}$

Variable	Comp1	Comp2	Comp3	Comp4	Comp5
$rESI_t$	-0.0578	0.5898	0.0136	0.1014	-0.7986
$rNIPO_t$	0.1552	0.5448	-0.1422	-0.7477	0.2898
$rE/D\text{-}Ratio_t$	-0.1786	0.4941	-0.4159	0.5889	0.4427
$rCCI_{t-1}$	0.0342	0.327	0.8786	0.1656	0.2787
$rTURN_{t-1}$	0.6832	0.0619	-0.1771	0.1145	0.0294
$rRIPO_{t-1}$	0.6875	-0.0228	0.0575	0.2082	-0.0606

Table 12: Score coefficient matrix and the sum calculated *isent* for $rESI_t$, $rNIPO_t$, $rE/D\text{-}Ratio_t$, $rCCI_{t-1}$, $rTURN_{t-1}$, and $rRIPO_{t-1}$

	Comp1	Comp2	Comp3	Comp4	Comp5	sum
r_i/sum r_i	0.3128	0.2764	0.1687	0.1249	0.1172	
$rESI_t$	-0.0181	0.1630	0.0023	0.0127	-0.0936	0.0663
$rNIPO_t$	0.0486	0.1506	-0.0240	-0.0934	0.0340	0.1157
$rE/D\text{-}Ratio_t$	-0.0559	0.1366	-0.0702	0.0736	0.0519	0.1360
$rCCI_{t-1}$	0.0107	0.0904	0.1482	0.0207	0.0327	0.3026
$rTURN_{t-1}$	0.2137	0.0171	-0.0299	0.0143	0.0034	0.2187
$rRIPO_{t-1}$	0.2151	-0.0063	0.0097	0.0260	-0.0071	0.2374

The equation (5) for *RSent* as below:

$$RSent = 0.0663 * rESI_t + 0.1157 * rNIPO_t + 0.1360 * rE/D - Ratio_t + 0.3026 * rCCI_{t-1} + 0.2187 * rTURN_{t-1} + 0.2374 * rRIPO_{t-1} \quad (5)$$

Table 13: Correlation coefficient matrix for *RSent* with six variables

Variable	*RSent*	$rESI_t$	$rNIPO_t$	$rE/D\text{-}Ratio_t$	$rCCI_{t-1}$	$rTURN_{t-1}$	$rRIPO_{t-1}$
$rESI_t$	0.2369	1					
$rNIPO_t$	0.4636	0.2825	1				
$rE/D\text{-}Ratio_t$	0.1802	0.2814	0.2089	1			
$rCCI_{t-1}$	0.5239	0.1779	0.1339	0.0422	1		
$rTURN_{t-1}$	0.7318	-0.0190	0.1937	-0.0567	-0.0384	1	
$rRIPO_{t-1}$	0.7280	-0.0484	0.0607	-0.1785	0.0740	0.7423	1

In the first column, all six variables have correlation coefficients greater than 0 with the constructed *RSent*. $rTURN_{t-1}$ and $rRIPO_{t-1}$ have the relatively highest correlation coefficients, $rCCI_{t-1}$ and $rNIPO_t$ are in the median, and $rESI_t$ and $rE/D\text{-}Ratio_t$ have the relatively smallest correlation coefficients.

According to ***Table 13***, the correlation coefficients between each variable and *RSent* are still positive. It indicates that the *RSent* index still has sounded model characteristics when controlling for the effects of macroeconomic factors. The increase in each variable $rESI_t$, $rNIPO_t$, $rE/D\text{-}Ratio_t$, $rCCI_{t-1}$, $rTURN_{t-1}$, $rRIPO_{t-1}$ at this time, also illustrates that: If future financial prospects, stock market IPO conditions, corporate decisions, and market activity are tending positive, the investor sentiment will also increase. This finding is consistent with what we discussed in Section 4.2. It shows that the index is still valid after controlling macroeconomic factors and has the ability to account for the relationship with each variable. And the difference in the correlation coefficient of each variable before and after control is the corresponding influence after removing the selected macroeconomic data.

4.4 Analysis of the relationship between the investor sentiment index and the Swedish stock market

After we have obtained a valid investor sentiment index, we would like to further explore whether this index has an impact on the Swedish stock market performance. Theoretically, fluctuations in investor sentiment will influence investors' decisions to either buy or sell stocks, which will be reflected in fluctuations in the market share price. Thus, we expect that the changes in the constructed investor sentiment index have some corresponding correlation with the market share price. Our purpose is to demonstrate that fluctuations in the investor sentiment index can explain, to some extent, the fluctuations in stock prices.

We use OMXS 30 and OMXS PI to represent the Swedish stock market share price performance. OMXS 30 is the Stockholm Stock Exchange's leading share index, which consists of the 30 most actively traded stocks on the Stockholm Stock Exchange. The OMXS PI covers the stocks listed on the Stockholm Stock Exchange, which measures the overall performance of the Swedish stock market. It can track the overall trend of the share price. Because the value size of the *RSent*, OMXS 30, and OMXS PI data varies greatly. We use min-max normalization to reduce the space for each set of data. This allows for a better comparison of the impact of index changes on stock prices. It also reduces the effect of differences in the absolute values of different indexes. The min-max normalization equation applied to these three sets of data is also equation (4):

$$x_{normal} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{4}$$

Then, we have the stacked line figure of the processed *RSent*, OMXS 30, and OMXS PI in ***Figure 1***.

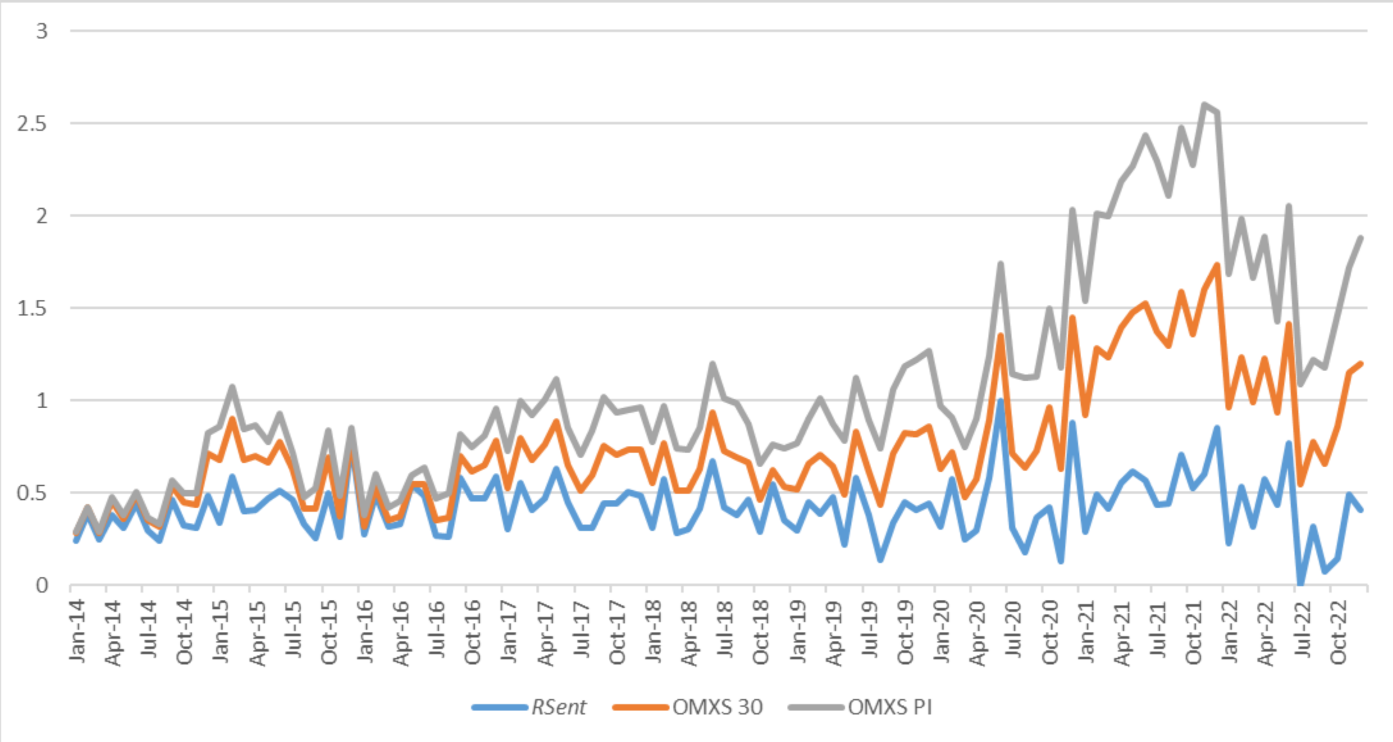

Figure 1: The trendlines of *RSent*, OMXS 30, and OMXS PI. The vertical coordinates indicate proportions, and the horizontal coordinates indicate time.

It is clear from the figure that the three lines share a common trend to a large extent. From April 2014 to August 2014, the trend lines of the investor sentiment index and the two stock indexes largely overlap. From August 2014 to April 2020, all three indexes fluctuate relatively frequently, and the fluctuation trends are very similar. Over the period April 2020 to November 2021, the overall volatility of the OMXS PI and OMXS 30 indices increases, while the upward trend of *RSent* is not clear. The inconsistency of this period may be due to the unusual market volatility caused by the outbreak of covid-19. Investor sentiment may be more volatile as a result of this particular event. Moreover, investor sentiment in response to the market is very different from what would be seen in a normal economic cycle. However, the trend of this volatility in the figure remains very similar. This indicates that investor sentiment is still somehow related to the market in the particular case, not absolutely unrelated. Moreover, from November 2021 until September 2022, the three lines are nearly mutually parallel.

To further illustrate, we use linear regression to discuss whether there is some more specific relationship between the investor sentiment index and the two stock indexes. Is the existence of a linear relationship significant? If it is significant and *RSent* investor sentiment index is used as a relevant factor influencing the share price index. Then its regression coefficient should be positive. It would indicate that when investor sentiment is high, the market is seen as more profitable by investors and stock prices will rise due to the influx of more investor money. We run the regressions of OMXS 30 on *RSent* and OMXS PI on *RSent*, and the results of the regression are shown in ***Table 14*** and ***Table 15***:

Table 14: Regression result of OMXS 30 on *RSent*

OMXS 30	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Rsent	0.5710	0.2752	2.07	0.040	0.0254	1.1165
Constant	0.3337	0.0244	13.69	0	0.2854	0.3821

Table 15: Regression result of OMXS PI on *RSent*

OMXS PI	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
RSent	0.5931	0.2724	2.18	0.032	0.0531	1.1331
Constant	0.3179	0.0241	13.17	0	0.2701	0.3658

In the significance test of OMXS 30 and *RSent* regression, the p-value is 0.040, which is less than 0.05, indicating that OMXS 30 and *RSent* have a linear relationship at a 95% confidence level. The p-value of OMXS PI and *RSent* equals 0.032, less than 0.05, suggesting OMXS PI and *RSent* also have a linear relationship at a 95% confidence level. This suggests that the constructed *RSent* has a correlation with the Swedish stock market prices. And this index can be used as a factor to explain the market share price changes. It can show that investor sentiment has an impact on the stock market. From the data in ***Table 14*** and ***Table 15***, we can find that the linear correlation coefficients between OMXS 30 and OMXS PI with *RSent* are both positive (0.5710 and 0.5931). This indicates that when investor sentiment is higher (as shown by the higher value of the *RSent* index), it leads to higher market stock prices. This is in line with the expectation. The findings indicate that investor sentiment index has a positive impact on the market, and the construction of the index is effective.

5. Conclusion

This thesis mainly develops an investor sentiment index for Sweden and analyzes the relationship between investor sentiment and stock market performance. We choose six variables that can reflect investor sentiment for the Swedish stock market: economic sentiment index (*ESI*), consumer confidence index (*CCI*), turnover (*TURN*), IPO number (*NIPO*), IPO return (*RIPO*), equity-to-debt ratio (*E/D-Ratio*) and use monthly data for all variables from January 2014 to December 2022. Comparing the impact of lead variables and lag variables on investor sentiment, we find that the consumer confidence index, turnover, and IPO return should use lead variable forms: CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$. And the economic sentiment index, IPO number, and equity-to-debt ratio should use lag variable forms: ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$. We then applied these six variables ESI_t, $NIPO_t$, $E/D\text{-}Ratio_t$, CCI_{t-1}, $TURN_{t-1}$, and $RIPO_{t-1}$, to construct a preliminary investor sentiment index *ESent* by PCA. The results show that there is a positive correlation between *ESent* with each variable, in line with model expectation.

Moreover, we control the macroeconomic factors to focus on investors' own sentiment and construct investor sentiment index *RSent* by conducting *PCA*. The controlled macroeconomic factors are consumer price index (*CPI*), producer price index (*PPI*), industrial production (*IP*), and employment rate (*EM*). It is worth noting that *RSent* still has a positive correlation with all six source variables, indicating the model's effectiveness after controlling macroeconomic factors. When we analyze the relationship between the investor sentiment index and the Swedish stock market, we plot the trendlines of the sentiment index *RSent*, OMXS 30 index, and OMXS PI index, which show that the investor sentiment index and stock market performance are closely related. And according to linear regression analysis, there is a positive linear relationship between investor sentiment and OMXS 30, OMXS PI. These results confirm that the index we constructed has a positive impact on the Swedish market and it is credible to reflect Swedish investor sentiment.

However, there are still several concepts that can be explored in the future. Firstly, the predictive ability of the constructed index of the Swedish market for future stock performance is worth investigating. Secondly, during a few periods of time, changes in sentiment and the stock market index do not coincide. Hence the reasons for this need to be explored. Finally, investor sentiment may have different impacts on stocks from different industries, specific impacts can be discussed in the context of different industry characteristics. For example, Huang et al. (2014) revealed noteworthy findings regarding the Chinese stock market. In the context of resource-based industries, it was observed that investor sentiment significantly influences stock returns during bear market conditions. On the other hand, in consumer goods industries, the impact on market returns tends to remain relatively stable.

We currently offer a method for constructing a Swedish investor sentiment indicator and explain the relationship between this indicator and the stock market. On this basis, it is worth discussing further how to focus on specific periods (e.g., covid, economic crisis) and specific industries in future research. It is also worth considering the specific mechanisms and pathways by which the investor sentiment index affects markets.

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