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The carbon risk premium: How much has already been realized in Sweden?

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Abstract

This research studies the asset pricing implications of firm's emission intensity. It studies the Swedish equity market, a front-runner in carbon pricing, in which firms are subject to the EU ETS and the currently highest carbon tax rate, from 2005 to 2021. The research introduces a new specification of the Group Fixed Effects (GFE) estimator from Bonhomme et al. (2022), marrying the methodology of Patton and Weller (2022); the EM-GFE estimator. The EM-GFE estimator accounts for the time-varying unobserved heterogeneity and finds a negative effect of emission intensity on equity returns. Further results show that emission intensity increasingly affects earnings as the carbon price increases. This study attributes its negative effect of emission intensity on equity returns to this finding and hypothesizes that the carbon price increases realize the carbon risk.

Keywords: Emissions, emission intensity, carbon risk, cross-section of equity returns, unobserved heterogeneity, GFE estimator, expectation maximization, risk realization.

Contents

1 Introduction

The combat against climate change relies heavily on the commitment of governments, companies and individuals. Countries need to drastically reduce their Green House Gas (GHG) emissions, to reach the climate goals set out in the Paris agreement of 2015. By 2030 countries need to have reduced 55% of their GHG emissions compared to 1990, and by 2050 each country should be carbon neutral. For many firms there is a fundamental conflict between productivity and profitability and their sustainability aspirations. The implementation of carbon taxes and the Emissions Trading Systems (ETS) give firms a financial incentive to become more environmentally sustainable by putting a price on their emissions. A carbon tax is a Pigouvian tax, a tax that puts a price on market activities which generate societal externalities; examples of Pigouvian taxes are plastic taxes, tobacco taxes and sugar taxes. The EU ETS is a cap-and-trade system. The cap refers to the maximum amount of allowed emissions per year for the installations covered by the ETS, 'trade' refers to a market determining the price of emissions, the allowance price. The EU ETS was implemented in 2005, thereby the first international ETS in the world. Although it is the oldest international ETS, it has only been in place for less than 20 years. Considering the history of equity markets which date back centuries, the EU ETS can be regarded as a new market. The EU ETS is a cornerstone of the EU's policy to combat climate change and is continuously evolving. This makes carbon pricing a central point of research in various research disciplines such as environmental research, fiscal-policy research and financial research. This research focuses on the effects of carbon pricing in equity markets. Carbon pricing induces various risks and opportunities to firms: the price of emissions, the physical risk of rising temperatures, the growing pressure from investors to become (environmentally) sustainable and the uncertainty about future legislation. The variety of risks makes the topic of environmental sustainability of great importance to firms.

The EU ETS covers all 27 EU member states plus Iceland, Norway and Liechtenstein. Currently, an allowance, which gives the holder the right to emit one tonne of carbon emissions, has a price of around €90 (August 2022). The EU ETS allowance price is relatively high compared to the Chinese, Korean and Californian (the biggest other ETSs in the world), which are all below €30 per tonne of emissions. Since the implementation of the Chinese ETS in 2021, the EU ETS no longer has the most extensive emissions coverage. In 2022, The Chinese ETS has a coverage of 4500 Mt (Metric Tonnes), the EU ETS has a coverage of around 1500 Mt of emissions and the Korean ETS (the third largest) has a coverage of 589 Mt of emissions[1]. In March 2022, the EU council reached an agreement on the Carbon Border Adjustment Mechanism (CBAM), a carbon tariff on carbon-intensive imported products, which will be put in place in 2026. The CBAM would positively affect the coverage of emissions in the EU ETS and is likely to affect equity markets significantly. The EU ETS and its relatively long history, high allowance price, coverage of emissions and evolving nature make it a front-runner in the field of carbon pricing.

Carbon pricing has thus far focused on ETSs where markets determine the price of emissions. However, various countries have a carbon tax in place where governments determine the price of emissions;

[1] https://icapcarbonaction.com/en/ets

among these countries are Switzerland, South Africa, The Netherlands and Sweden. Sweden is one of the earliest adopters of carbon pricing and started imposing an emission tax of around €24 in 1991 and currently levies the highest tax with Switzerland, of around €117. The Swedish carbon tax and the EU ETS complement each other in carbon pricing; the EU ETS focuses primarily on industrial companies, and the carbon tax covers the entire economy. However, the carbon tax exempts the emissions subject to the ETS. The carbon tax covers around 40% percent of the fossil emissions and together with the EU ETS they cover 95% of the fossil carbon emissions in Sweden. In comparison, China, Switzerland and California respectively cover around 28%, 45% and 74% of their carbon emissions[2] [3] [4].

This research will study the effect of carbon pricing on equity markets in the Swedish equity market, since the carbon pricing measures in Sweden cover a large amount of the national emissions with a high price. The main focus of this research is to assess whether a carbon risk premium is present in the Swedish equity market, i.e. are emission-intensive firms traded with a premium for the carbon risk they face? A carbon risk premium would cause carbon-intensive firms to have higher equity returns as they are considered riskier, i.e. the risk-return relation. However, Hsu et al. (2022) argue in their research that the risk of changing (carbon) regulation into a more stringent regulation causes a carbon risk premium. As Sweden has one of the most stringent carbon regulations around the world, in terms of carbon pricing, it could well be that the carbon risk premium is not, or is less, present in Sweden. Furthermore, as carbon emissions are priced, the amount of emissions per revenue (emission intensity) can affect profits negatively by the costs that accompany emissions. When the profitability of a firm declines, its valuation would decline along. Oestreich and Tsiakas (2015) find a positive carbon risk premium and attribute this to earnings effects, even though they consider the EU ETS over a brief period in Germany, it suggests carbon pricing can significantly affect the revenue of certain companies. Considering that Sweden also levies the highest carbon tax adds to the motivation to research whether emission intensity affects equity returns through firms' profitability. Therefore, this research examines the effect of carbon (intensity) on equity returns, to assess if a carbon risk premium is present and whether this effect is overshadowed by the effect of increasing emission costs on profitability.

This research estimates a Fama-Macbeth specification of the Grouped Fixed Effects (GFE) estimator from Bonhomme and Manresa (2015) to examine the effect of emission intensity on equity returns over the period from 2005 to 2021. The GFE estimator can account for time-varying unobserved heterogeneity, i.e. unobserved differences between firms that affect their characteristics or equity returns, differently over time. Bonhomme et al. (2022) add to the research of the GFE estimator and introduces a 2-step GFE estimator, which groups individuals using the K-means algorithm from Lloyd (1982). Patton and Weller (2022) employ an Expectation Maximization (EM) algorithm to estimate time-varying group-specific coefficients in an asset pricing setting. The EM algorithm applied by Patton and Weller (2022) is closely related to the K-means algorithm from Lloyd (1982). This research

[2]Intergovernmental Panel on Climate Change (IPCC) found in 2018 that around 89% of global CO2 emissions came from fossil fuels and industry.

[3]https://www.government.se/48e407/contentassets/419eb2cafa93423c891c09cb9914801b/210111-carbon-tax-sweden--general-info.pdf

[4]https://government.se & https://carbonpricingdashboard.worldbank.org

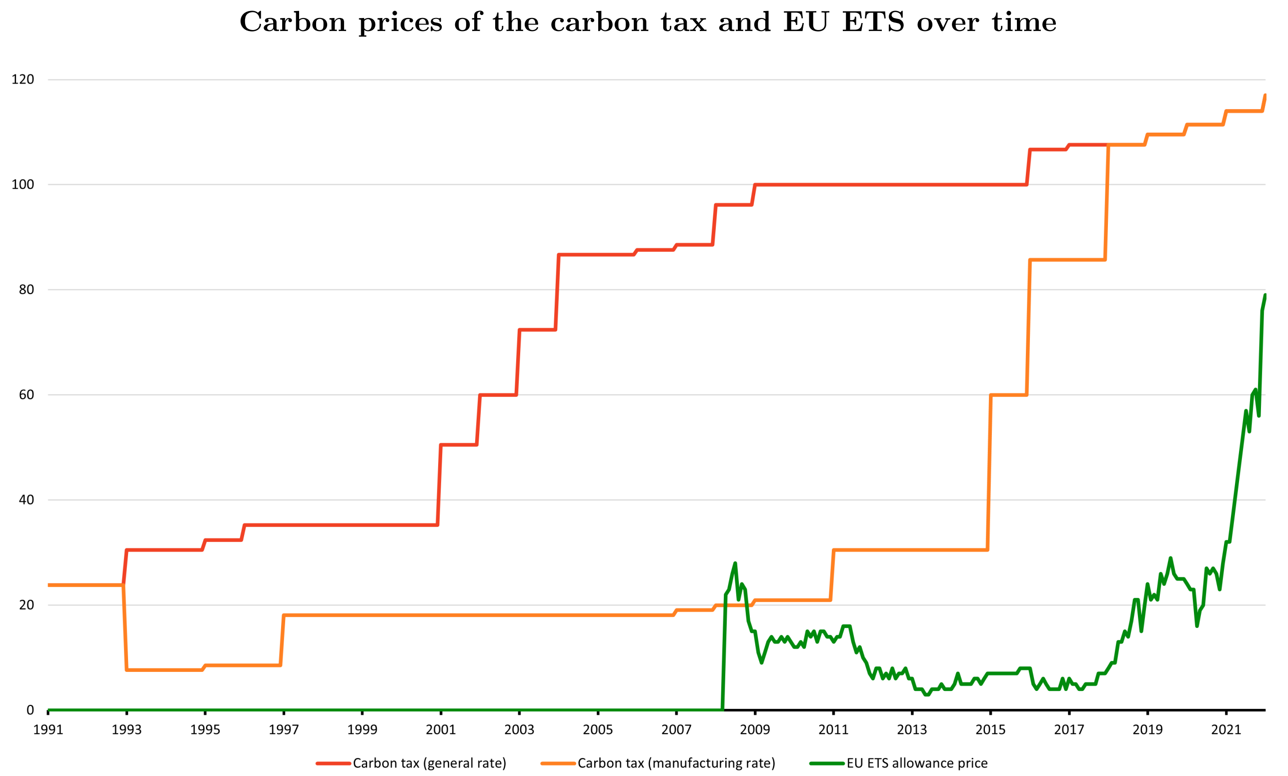

Figure 1: The price of carbon emissions from 1991 to 2022. The figure shows The EU ETS price from January 2008 to August 2022 and it shows the Swedish carbon tax rates from January 1991 to August 2022. The prices are denoted in Euro per tonne of emissions, the Swedish tax is conversed with an exchange rate of 10,50 SEK/EUR.

uses the theoretical framework of the GFE estimator from Bonhomme et al. (2022) and extends it by estimating it with the EM algorithm, closely related to the work of Patton and Weller (2022). The research finds that the EM-GFE model is well suited to account for unobserved heterogeneity. The model results present a negative effect of emission intensity on equity returns. This research further argues that this relation can be attributed to the increasing price of emissions and inherently, the changing amount of carbon risk.

The research continues by describing the carbon pricing mechanisms in Sweden in more detail and elaborating on literature related to this research in section 2. Section 5 presents the methodology applied in this research and the statistical background. Section 6 presents and analyzes the results of the research and section 7 contains the conclusion of this research and provides future research propositions.

2 Background and Literature

This section covers some background information on the the EU ETS in subsection 2.1. The background information is of importance for the research to interpret the dynamics of the effect of emission intensity on the equity market. The section continues by reviewing related literature that touches upon this research in subsection 2.2.

2.1 EU ETS background

The EU ETS, implemented in 2005, is currently in its fourth phase, which started in 2021. Phases one and two of the ETS, covering the period from 2005 until 2012, offered carbon allowances largely for free. Phase 3 (2013-2020) cut back the amount of freely handed out allowances and implemented a benchmark approach to assign free allowances; the benchmarking approach assigns free allowances up to the average level of emissions from the 10% most efficient installations in the same industry. Appendix figure 11 shows that the part of free allowances diminished over the years. For the larger part of phase three of the ETS, the allowance price has been below €10 per tonne of emitted carbon. The economic crisis of 2008 led to a significant reduction in emissions resulting in an allowance surplus, which resulted in the low allowance price. The carbon price reached the price of €10 again in 2018, as presented in figure 1. Short before phase four in 2019, the European Commission incorporated a Market Stability Reserve (MSR) in the ETS. The MSR controls the number of allowances in circulation to ensure price stability of the allowances. Each year the Total Number of Allowances in Circulation (TNAC) is calculated, which boils down to the amount of freely handed out allowances and auctioned allowances minus the verified emissions (for which allowances are handed in). The TNAC signals whether the demand for allowances meets the supply and determines whether the number of allowances to be auctioned the following year should be lowered or increased. If the TNAC exceeds a certain threshold, the number of allowances (that will be auctioned) will be reduced and added to the MSR instead. If the TNAC is below a threshold, the number of allowances will be increased for the next year with allowances collected from the MSR. However, to this day, the TNAC has been above the threshold each year and caused the amount of auctioned allowances to be lowered. Phase four added more power to the MSR to stabilize the allowance market. Furthermore, phase 4 increased the annual allowance decline by 2.2% instead of 1.74% to reach climate goals at a faster pace. These more progressive legislation changes aided the increase of allowance prices. By the start of phase four in 2021, the allowance price had risen from below €10 to a price above €30. The allowance price reached €98.49 at its peak in 2022, after which it declined to a price of around €90, around which it currently stands. The EU ETS not only saw significant changes in the price of allowances over the years, but also evolved its regulation and expanded its coverage over countries, sectors and firms.

The proposed CBAM, Carbon Border Adjustment Mechanism, is a carbon import tariff planned to be implemented in 2026. The CBAM would enable the EU to cut back on free allowances as it would no longer result in carbon leakage. The evolving nature of the EU ETS has been crucial in stabilizing the allowance market, showing it is heavily subject to regulation changes. Currently, the EC has proposed to sell an extra 250 million allowances from the MSR to fund the transition to phase out Russian fossil fuels. The influx of extra allowances could result in destabilization of the EU ETS, as pointed out by the urgent call to veto this inference from the Climate Action Network Europe[5]. The impact of the MSR and the destabilizing effects that an allowance injection could cause show the vulnerability of this young market to regulatory inferences.

Considering the formulated hypotheses, one can obtain a better understanding of the risk that an investor faces when increasing legislation prices a greater part of the carbon emissions and at a higher price. The EU ETS reached a price of €98.49 in 2021 and is currently priced around €90; what if prices remain at these levels? The EU ETS steadily expands its coverage and steadily reduces the

[5]https://caneurope.org/urgent-call-to-veto-commission-proposal-releasing-allowances-from-market-stability-reserve-to-finance-repowereu/

number of free allowances. Moreover, by putting the proposed CBAM in place, the EU ETS could decrease the number of free allowances as it would no longer result in carbon leakage. By researching the Swedish market, one could get a better understanding of the dynamics of carbon pricing and the risks that an investor faces.

2.2 Literature review

Various papers research the asset pricing implications of emissions and the accompanying risks in various market settings. Bushnell et al. (2013) and Oestreich and Tsiakas (2015) study the EU ETS in the EU as total and Germany, Bolton and Kacperczyk (2021) and Hsu et al. (2022) research the U.S. equity market, Wen et al. (2020) study the Shenzhen pilot ETS, the pilot of the Chinese ETS and Blitz and Hoogteijling (2022) research a worldwide theoretical setting. Some of this research focuses on the effects of carbon pricing and the number of firms' emissions on equity markets to research the presence of a 'carbon risk premium'. A carbon risk premium is interpretable as the compensation in equity returns that an investor requires for the carbon risk of a certain equity or portfolio; the risk that future returns will be negatively affected by changing regulations or increasing carbon prices.
Oestreich and Tsiakas (2015) find that (dirty) companies, receiving many free allowances, faced windfall returns during the first phase of the ETS compared to firms that did not receive free allowances; this phenomenon was already pointed out by Bovenberg and Goulder (2001) who showed that a relatively small fraction of free allowances could already compensate the profits for many industries. Oestreich and Tsiakas (2015) show through the formation of a Dirty Minus Clean (DMC) factor that a significant carbon risk premium is present for phase one of the EU ETS and fades away in phase two, which is attributable to the higher cash flows. However, they can not exclude that their findings might have been a one-off event. Bushnell et al. (2013) find that the steep decline of allowance prices in a three-day window in April 2006 had a significant negative effect on the equity returns of carbon-intensive firms. They argue that the negative effect on equity returns of carbon-intensive firms could be attributed to lower cash flows of firms that receive the lion's share of their allowances for free. Bolton and Kacperczyk (2021) research the cross-section of U.S. equity returns between 2005 and 2017 and find that high emitting companies, being exposed more to carbon risk, provide significantly higher equity returns while controlling for other risk factors and industry-specific effects. Hsu et al. (2022) create long-short portfolios of U.S. firms with high emissions versus low emissions per sector from 1992 to 2017 and also find that the high-emitting firms outperformed the low-emitting firms. The research from Wen et al. (2020) shows that the participation of companies in the Shenzhen pilot ETS positively affected their equity returns by estimating a Difference in Difference model (DiD) between participating and non-participating companies while also accounting for industry characteristics and some classical risk factors. Wen et al. (2020) follow the methodology of Oestreich and Tsiakas (2015) in forming a DMC factor and find a positive carbon risk premium as well, which they explain by showing that the ETS-participating companies are, in general, the highest emitting ones. Blitz and Hoogteijling (2022) theoretically impose a $100 tax on carbon and assess the effects it would have on the portfolio properties and returns of a value investor. They show that, from a value investor's perspective, the

effect of a carbon tax is equivalent to a carbon restriction in the optimization of the portfolio. They find that a theoretical carbon tax of $100 results in a carbon footprint reduction of around 50% for their optimal long-short value portfolio.

Hsu et al. (2022) and Bolton and Kacperczyk (2021) show the presence of a carbon risk premium in the U.S. equity market while controlling for various risk factors, industry effects and firm characteristics. Bolton and Kacperczyk (2021) find that the carbon risk premium can not be explained by divestments on their own, but does not conclude on what causes the carbon risk premium. Hsu et al. (2022) empirically examine whether the positive emission-return relationship can be attributed to several, in the literature, suggested explanations [6]. Hsu et al. (2022) did not find any of the suggestions explanatory. However, they find that high-emission firms have higher risk premia connected to a regulation regime shift into a stringent regulation. They find this result using a general equilibrium asset pricing model with uncertain cash flows. This research applies the Group Fixed Effects (GFE) estimator as introduced by Bonhomme and Manresa (2015) and further researched in Bonhomme et al. (2022). The GFE estimators are able to account for (time-varying) unobserved heterogeneity and thereby are able to exploit the cross-sectional and serial dependence in the data. Bonhomme and Manresa (2015) introduce the GFE estimator and explore asymptotic properties to assess the consistency of the estimator; they apply a GFE estimator to research the link between income and democracy across countries. Bonhomme et al. (2022) introduces the two-step GFE estimator and studies the GFE estimator in settings where the assumed unobserved heterogeneity is not necessarily discrete, i.e. based on a finite amount of effects. Bonhomme et al. (2022) further studies the asymptotic properties of the GFE estimator, they show that under certain assumptions the GFE estimator is able to provide consistent results when the unobserved heterogeneity is not assumed to be discrete. They apply the GFE estimator in a dynamic model of wages and labour participation where the unobserved heterogeneity is not restricted to be discrete and compare this with general FE estimators. Bonhomme et al. (2022) also studies the GFE estimator in a probit model where the heterogeneity is not discrete but low-dimensional; they find that low-dimensionality is a needed assumption for the GFE estimator to be consistent. The GFE estimators from Bonhomme and Manresa (2015) and Bonhomme et al. (2022) group individuals using the K-means algorithm, a machine learning method introduced by Lloyd (1982). However, the GFE estimator is not restricted to classify individuals using the K-means algorithm. Patton and Weller (2022) classify firms into groups using the Expectation Maximization (EM) algorithm, extending the K-means algorithm. Patton and Weller (2022) use the EM algorithm as they classify firms on their error dependence structure, which requires an iterative approach. Patton and Weller (2022) research whether equal compensation across assets for various risk exposures is a valid assumption. They estimate an asset pricing model based on the Fama-Macbeth method from Fama and MacBeth (1973) and adapt the model to account for cross-sectional heterogeneity by allowing for group-specific risk exposures. Patton and Weller (2022) find evidence that cross-sectional

[6]Among the suggested explanations for the carbon risk premium that Hsu et al. (2022) did not find to be explanatory are; investors' emission preferences, under-reactions to emission abatement, retail investors' behavioural bias, corporate governance, technology obsolescence, financial constraints, economic and political uncertainty, adjustment costs and other potentially related systematic risks.

variation affects risk exposures, implying that classic factor models are incomplete and miss important cross-sectional variation in the expected equity returns. This research methodology is closely related to the researches from Bonhomme et al. (2022) and Patton and Weller (2022). It builds upon the framework from Bonhomme et al. (2022) and combines it with an asset pricing method for risk price estimation, equivalent to the research of Patton and Weller (2022). This research deviates from Patton and Weller (2022) in its objective and model specification. This research focuses on finding a universal (market-wide) effect of emission intensity on equity returns. Therefore, the model specification in this research allows for group-specific intercepts instead of group-specific risk prices like Patton and Weller (2022). This research expands the literature on discretizing unobserved heterogeneity by estimating a GFE estimator which classifies groups using the EM algorithm. Furthermore, this research expands the literature on asset pricing consequences of increasing carbon prices by examining the dynamics of a carbon risk premium.

3 Carbon risk premium hypotheses

Research into a carbon risk premium has emerged as a topic of great interest over the last years, as the world has become well aware of the detrimental effects of carbon emissions. Various countries intend, or have already, enacted legislation to cut emissions. The carbon risk premium can be attributed to a variety of things, among which: physical risk of pollution, risk of future sustainability-related expenditures, risk of costly environmental litigation, the pricing of firms' carbon emissions and much more. The main goal of this thesis is to accurately model the effect of emission intensity on equity returns, accounting for possible heterogeneous effects. Thereby, this research is able to infer, based on a consistent estimator, the dynamics between increasing carbon prices and a carbon risk premium[7]. Specifically, the research tries to shed light on the effect of carbon pricing (risk) on equity returns through the following three parts: the effect of the risk of increasing emission prices, the effect of actually increasing emission prices and the effect of the level of emission pricing that is in place. A hypothesized carbon risk premium is, in essence, different to more familiar risk premia. Risk premia, such as the size or value risk premia, can be explained by fundamental risk. In contrast, a carbon risk premium can be explained as being caused by externalities rather than fundamentals. As Bolton and Kacperczyk (2021) point out in their research, looking back to the 1990s, there seemed to be no significant carbon risk premium. However, they do find a significant carbon risk premium between 2005 and 2017, while Fama and French (1992) find the size and value risk premia to be present from 1963 to 1991. This difference highlights the difference in the essence of the carbon risk premium and more familiar risk premia. This section tries to rationalize the effects of carbon pricing (risk) on equity returns.

[7]This research will refer to carbon pricing risk as the more general term: carbon risk

3.1 Carbon risk premium rationalization

Following the rationalization of certain risk premia by Fama and French (2015), one can get a grasp on the relation between carbon pricing and equity returns. Fama and French consider the dividend discount model and modify this according to the rationale of Miller and Modigliani (1961), which states that the market value of equity is equal to the discounted value of expected future dividends per share;

$$\begin{aligned} m_t &= \sum_{\tau=1}^{\infty} \mathbb{E}\left(\frac{d_{t+\tau}}{(1+r)^{\tau}} \right) \\ &= \sum_{\tau=1}^{\infty} \mathbb{E}\left(\frac{EPS_{t+\tau} - \mathrm{d}b_{t+\tau}}{(1+r)^{\tau}} \right). \end{aligned} \tag{1}$$

The market value per share at time t, denoted as m_t, is determined by all expected future dividend payments per share, $d_{t+\tau}$, discounted by the average internal rate of returns on dividends, r, i.e. the long term average equity return. The second expression expresses future expected dividends as the residual of the EPS_t minus the growth in book value per share b_t. From the expression, one can infer relations between the market value of equity, the expected future firms' earnings and the expected long-term average equity. Equation 1 makes two statements about changing earnings outlook that are of interest to this research. Assume a firm's future earnings outlook worsens due to expected (higher) carbon pricing and assume its change in book value and expected long-term average equity returns stay the same, then the firm's market value has to decrease. Next, again assume a firm's future earnings outlook worsens due to expected (higher) carbon pricing and assume its change in book value and the firm's market value to stay the same, then its expected long-term average equity returns have to decrease. The outlook that firms' earnings will decrease when the risk is realized, i.e. the expected (higher) carbon price is realized, causes the decrease in long-term average equity returns. However, up to the point in time where the risk is realized, the firm's earnings will remain at the same level and compensate investors for the risk they bear through the higher equity returns.

The insights from the two statements based on 1 can be combined, where one can assume that the emergence of a carbon risk premium has various effects; a negative effect on market value, a negative long-term effect on expected equity returns and a positive effect on equity returns up to the point where the risk is realized, i.e. a (higher) carbon price is put in place.

The risk premium causes emission-intense equity to have higher expected equity returns than their peers with lower emission intensities. As the carbon risk premium has increased various times over the sample from 2005 to 2021 in Sweden, this would imply that the effects between emission intensity and equity returns would alternate between negative (when perceived carbon risk increases or carbon risk realizes) and positive (as emission intense firms have higher expected equity returns). Also, the carbon risk would diminish with the amount that the carbon price increases as it no longer poses a risk but realizes an actual earnings decrease. This relation implies that the emission intensity correlation with firms' earnings increases over time as various carbon price increases have taken place. Since the carbon tax affects the earnings after tax as opposed to the earnings before tax, the relation also implies that the effect of emission intensity on earnings after tax is greater than on earnings before tax.

Based on the insights formulated in this section, this research hypothesizes the following four statements concerning the relation between emission intensity, earnings and equity returns:

- The realizations of carbon (price) risk, the carbon price increases, cause a negative effect between emission intensity and equity returns.
- The expected carbon price (assumed to be increasing over the sample) increases the carbon (price) risk. This, together with statement one, thereby cause the effect of emission intensity on equity returns to alternate in sign over time.
- The increasing carbon price causes the correlation between emission intensity and earnings to grow over time.
- The correlation between emission intensity and earnings is greater with earnings after tax than with earnings before tax.

Together, these hypotheses suggest that the carbon risk premium, i.e. the equity return outperformance of emission-intense firms, found by Hsu et al. (2022) and Bolton and Kacperczyk (2021) (in samples with lower carbon price increases), to be less significant in Sweden. As some of the hypotheses on the dynamics of a carbon risk premium are difficult to prove or falsify, this research tries to shed light on the dynamics of a hypothesized carbon risk premium. The main goal of this research is to find a consistent estimator of the effect of emission intensity on equity returns by accounting for unobserved heterogeneity. Thereby, this research provides empirical evidence, based on a consistent estimator, to substantiate or refute the statements concerning the hypothesized carbon risk premium. Therefore, the research is only able to empirically assess the presence and dynamics of a carbon risk premium.

4 Data

This research covers the period from 2005 to the end of 2021. Although the Swedish carbon tax was initiated in 1991, data availability restricts the research to take 2005 as the first date in the sample. The research is built upon financial data of Swedish equity from Bloomberg and firm-level emission data, covering scope 1 + 2 emissions from MSCI ESG, Refinitiv-Eikon, ISS Datadesk and Factset. This study collects annual Swedish sector-level data from the SCB (Statistics Sweden) for the available years (1993 to 2020) on: emissions, total paid carbon taxes and net turnover. From the available data of the SCB, one can infer the average paid tax per sector, the total amount of taxes paid per sector and the percentage of net turnover, which are taxed by the carbon tax.

The financial data of the individual firms are collected from Bloomberg. The collected data consists of monthly equity prices, monthly Market capitalizations (Mcap) denoted in billion SEK, quarterly Book to Market ratios (BM), quarterly Returns On Equity (ROE) denoted in percentage of earnings per market capitalization and quarterly Earnings Per Share (EPS) pre-tax and after-tax denoted in millions SEK (MSEK). Yield data from the Swedish 10-year government bond is collected from Bloomberg, serving as the risk-free rate and is presented in Appendix A.1. From the Bloomberg data one can retrieve the log excess returns $r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}} - r_{f,t}\right)$, where $P_{i,t}$ denotes the price of firm i at time t

and $r_{f,t}$ is the Swedish 10-year (monthly) yield at time t. The research takes the Log excess returns as its dependent variable because of its economic interpretation, as it presents the outperformance of equity compared to a risk-free rate.

4.1 Emission data

Environmental reporting is still in an early phase, but each year the number of reporting firms grows. Therefore, the acquired emission data is less often estimated from peers but acquired through reports, which also increases the accuracy of other firms' estimated emissions. Through the sample period, the accuracy of the reported emissions has increased because of standardization and measuring initiatives such as ISO 14064 and the GHG Protocol[8]. As firm-level emission data is currently relatively scarce and inaccurate, the emission data in this research is collected and assembled from various providers to ensure the data is as complete and accurate as possible. The annual emission data is collected from Refinitiv-Eikon, MSCI ESG Leader, ISS Datadesk and Factset. The datasets can vary in availability per company, historic length per company, and how datapoints are obtained. Per data provider and firm of interest, there might be differences in the source of the emission data. Providers may obtain their data from reports, voluntary disclosures to CDP[9], from estimations based on a basic sector median, based on a firm's relation to industry peers and various other types of estimations. The disclosures of the data providers on the acquirement of the data are valuable to assemble the data and obtain more insight into the datapoints' accuracy. Collecting and assembling the emission datasets is a tedious process; the Swedish-listed firms available in Bloomberg are matched with the emission datasets based on their ISIN, ticker or firm name (depending on the availability of firm identifiers in the dataset). Once the datasets are matched across firms, the datapoint origins are collected and ranked on their accuracy (following the researchers' judgement). The emission data can then be assembled per firm using the most 'accurate' emission datapoints. In case of equal assumed accuracy, the datapoint from the most extensive dataset is selected; the datasets are ranked as follows: Refinitiv-Eikon, MSCI ESG Leader, ISS Datadesk and Factset. From the assembled emission dataset, one can obtain the emission intensity of a firm by dividing the emissions by the revenue. Emission intensity is expressed in tonnes of emissions per MSEK revenue.

4.2 Sample statistics

This research considers firms selected on two criteria; a minimum market capitalization of SEK 5 billion at the end of the sample and a minimum of six years of emission intensity data per firm. The research applies a minimum market capitalization as firms with a low capitalization in the market tend to have low liquidity and thereby tend to have significantly higher idiosyncratic volatility, which

[8]The ISO 14064, International Organization for Standardization (ISO), provides GHG accounting and verification standards since 2006. The GHG protocol is a collaboration between the World Resources Institute (WRI) and Business Council for Sustainable Development (WBCSD). The GHG protocol establishes a comprehensive, global, standardized framework for measuring and managing emissions.

[9]CDP is a not-for-profit organization that runs a global environmental disclosure system on climate change risks and opportunities.

Full sample descriptive statistics

	Mean	St. dev	Kurt	Skew	Min	Max	Cross-corr	Autocorr
Intensity	15.0	11.9	0.5	0.0	-0.3	1145.6	0.30	0.49
Mcap	53.3	23.5	0.9	0.9	0.0	733.0	0.53	0.96
BM	0.7	0.4	1.6	5.4	-2.0	51.3	0.33	0.92
ROE	8.1	21.6	0.3	13.9	-1138.5	2607.4	0.03	0.71

Table 1: This table contains the full sample (2005-2021) statistics per variable. The independent variables in the models are: Intensity, Mcap, BM and ROE, Intensity denotes the Emission intensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization). The table reports the following statistics: the mean, standard deviation (St. dev), kurtosis (Kurt), Skewness (Skew), minimum, maximum, average cross-sectional correlation (Cross-corr) and average autocorrelation (Autocorr).

Average correlation of variables over time

	Intensity	Mcap	BM	ROE
Intensity	1			
Mcap	-0.08	1		
BM	0.32	-0.10	1	
ROE	-0.07	-0.01	0.29	1

Table 2: The average correlation of the variables over time over the full sample (2005-2021), the correlations are taken per point in time over the firms after which the average is taken.

could disturb the implications of the models. The minimum intensity datapoints per firm ensures that a larger part of the cross-section, the amount of firms in the sample, contributes to the estimation of the effect of intensity on equity returns. The Refinitiv-Eikon and Bloomberg dataset contain over 1000 (primary) listed firms on Swedish markets. The imposed criteria reduce the number of firms in the cross-section to 77. Table 1 presents an overview of the variables of interest over the full sample, i.e. from 2005 to 2021 with the 77 firms. Appendix table 8 tabulates a more extensive overview with the statistics per sector. Table 1 shows that the average market capitalization in the sample is around ten times as large as the minimum criterion induced. The annualized ROE on average equals 8.1% with a standard deviation of 21.6%; ROE is the only variable for which the standard deviation exceeds the average. Therefore, ROE can be considered relatively volatile compared to the other variables. All variables are platykurtic compared to the standard normal distribution, meaning they have larger tales. The distribution of intensity levels is symmetrical around its mean, as opposed to Mcap, BM and ROE, which are positively skewed around their mean. The skewness observation is not unexpected, as negative values of these variables, in contrast to positive outliers, are impossible or non-sustainable for a firm. Appendix figure 6 shows the positive skewness, it shows a large cluster of firms at the relatively low levels of the Intensity, Mcap and BM variables but also has many positive outliers. All

Emission intensity across sectors

	Firms	Mean	St. dev	Min	Max	Cross-corr	Autocorr
Health Care	6	1.8	1.4	0.0	8.9	0.53	0.48
Industrials	25	10.9	9.2	0.0	446.4	0.27	0.44
Financials	11	6.5	5.3	-0.3	125.6	0.14	0.28
Energy	1	292.2	309.1	18.3	1145.6		0.79
Communication Services	3	2.2	1.4	0.2	8.5	-0.11	0.57
Materials	6	49.9	25.8	4.1	295.1	0.31	0.59
Information Technology	5	14.5	10.7	0.1	203.2	0.69	0.47
Real Estate	8	9.2	6.0	0.5	35.2	0.12	0.61
Consumer Discretionary	9	2.7	1.1	0.2	10.9	0.79	0.71
Consumer Staples	3	10.5	12.5	0.2	103.3	0.29	0.48
Full Sample	77	15.0	11.9	-0.3	1145.6	0.30	0.49

Table 3: This table contains emission intensity statistics and the number of firms per sector over the full sample period (2005-2021). The table reports the following statistics: the mean, standard deviation (St. dev), minimum, maximum, average cross-sectional correlation (Cross-corr) and average autocorrelation (Autocorr). The statistics are reported for the full sample and for each individual sector that is present in the sample.

variables showcase positive cross-sectional correlation and autocorrelation. The positive cross-sectional correlation implies a positive relation between the movements of a variable at the same time-point over firms. The positive autocorrelation indicates a positive relation between the values of a variable over time for a firm. Table 2 presents the average cross-sectional correlation of the variables, where the average is taken over the points in time. The table shows that all the variables are positively correlated with each other. Table 3 shows that the sample of 77 firms is not equally dispersed over the sectors. For example, the Utilities sector has no presence, there is one firm in the energy sector and there are 25 firms in the Industrials sector.

Table 3 presents descriptive statistics of emission intensity per sector; Appendix table 8 reports the same statistics for the other variables. The table shows that the average annual intensity equals 15.0 tonnes/MSEK, but logically varies across sectors. Dirty industries such as Energy and Materials have an average intensity of around 300 and 50, while Health Care and Communication Services have an intensity of around 2. Notable is a firm's reported negative intensity point in the Financial sector. A Financial firm reported a negative revenue for a certain year which caused the negative emission intensity. A negative revenue could occur in a unique situation; an example is a firm with lower earnings than its returned sales. Overall, the intensity variable shows a positive relation over time, the autocorrelation equals 0.49. The emission intensity also moves in the same direction across firms, with an average cross-sectional correlation of 0.30. However, the cross-sectional correlation of Intensity varies remarkably over the sectors, as opposed to the autocorrelations, which are more in line over the sectors. The varying cross-sectional correlation could imply that for some sectors, such as Consumer Discretionary (with a cross-sectional correlation equal to 0.79), intensity changes are more likely to be caused by systemic factors, such as macroeconomic changes. In contrast, the changes in intensity in other sectors, such as Real Estate with a cross-sectional correlation equal to 0.12, are more likely to be caused by idiosyncratic factors. Table 8 shows that the Energy, Real Estate, Financial and Materials sector tend to have a higher book-to-market ratio, as those firms tend to have an extensive amount of assets compared to their human capital and technology advancements; in contrast to the Health Care, Information Technology, Consumer Discretionary and Consumer Staples sectors. The following section 5, the methodology section, further investigates the possible implications of this observation.

5 Methodology

To research the carbon risk that an investor faces, this research tries to find whether a theoretical carbon risk affects the Swedish equity market. The research tries to explain equity market returns by firm emission intensity (emissions to earnings) to assess the presence of carbon risk affecting equity returns in the Swedish market. This section covers different estimators of the effect of emission intensity on equity returns; it covers the pooled OLS estimator, the Fama-Macbeth estimator and the GFE estimator. Petersen (2009) researches the methods that other papers in the Financial literature employ to estimate coefficients and standard errors in panel data sets[10], the research points out that the chosen method is often incorrect. Despite that Petersen (2009) researches papers published around two decades ago, between the years 2001 to 2004, various other studies into the effect of emissions on equity returns, conducted more recently, only account for discrete unobserved heterogeneity. Research of Hsu et al. (2022) and Oestreich and Tsiakas (2015) both rely on the FM approach conditioning on the industry of a firm. This research researches the dynamics of the dependence structure and does not restrict the heterogeneity to be discrete. Furthermore, it shows the implications of various types of dependence structures on the consistency of different estimators.

The first part of this section presents the estimators and shows under which assumptions, regarding dependencies, the estimators are unbiased and consistent. The first subsection, 5.1, presents the FM estimator and shows under which assumptions the FM estimator is consistent as opposed to regular OLS. The subsection considers fixed error dependencies (cross-sectional and serial) and presents assumptions under which the FM approach is not able to provide a consistent estimator. Subsection 5.2 relaxes the assumption of fixed dependencies and allows the unobserved heterogeneity to be time-varying. The subsection presents the model specification of the GFE estimator from Bonhomme and Manresa (2015) and shows under which assumptions this estimator is consistent as opposed to the FM estimator. Subsection 5.3 presents how the dynamics of the unobserved heterogeneity can be detected. The last subsections cover the GFE estimator in more detail and present the different estimators. Subsection 5.5 presents the K-Means (KM) GFE estimator from Bonhomme et al. (2022) and subsection 5.6 presents the Expectation Maximization (EM) GFE inspired by the research of Patton and Weller (2022).

[10]Petersen researched 207 papers from the *Journal of Finance*, *Journal of Financial Economics* and the *Review of Financial Studies* between the years of 2001 to 2004.

5.1 Fixed error dependencies

The effect of emission intensity on the equity returns can be investigated following an empiricist approach by performing the widely used Fama-Macbeth (FM) approach (Fama and MacBeth (1973)). The equations below present the FM regression, formulated in the case of a single independent variable,

$$\begin{aligned} r_{i,t} &= a_t + \hat{\theta}_t c_{i,t-1} + e_{i,t} \\ \hat{\theta}_{FM} &= \frac{1}{T}\sum_{t=1}^{T}\hat{\theta}_t. \end{aligned} \tag{2}$$

In the FM approach one estimates T cross-sectional regressions of log *excess* equity returns of firms on the characteristic $c_{i,t}$, which could be the emission intensity of firm i at time t. Considering the average effect over time of a characteristic on the equity returns, $\hat{\theta}$, as determined in the second part of the equation, one can find an indication whether the characteristic is able to explain the returns in the sample. The formulation in 2 is for a single characteristic, however one can add more characteristics to the regression to better cover the range of effects, for this reason, the research will also add $Mcap$, B/M and ROE as characteristics based on the 5-factor Fama-French model Fama and French (2015), leaving out $CAPEX$ (Capital expenditure) due to a lack of data. The two-step approach of FM accounts for cross-sectional dependence, which is likely to be present as common shocks and latent- or omitted variables could cause this dependence. By neglecting cross-sectional dependence and estimating a regular OLS regression, one would estimate biased standard errors of the regression coefficient θ, and could thereby wrongfully assume the coefficient to be significant as derived and shown by Petersen (2009). The FM approach is widely used in financial research as it compensates for cross-sectional dependence. However, the FM approach does not compensate for time-series dependence. According to Cochrane (2005), neglecting possible time-series dependence could not be so bad in researching equity returns as they are close to independent over time. However, the characteristics of firms, such as firm size, are more autocorrelated than their first-difference counterparts, such as size growth. Since this research regresses equity returns on autocorrelated firm characteristics, the model errors could be subject to time-series dependence caused by omitted or latent characteristics. Therefore, this research considers the effects of serial correlation, despite the statement of Cochrane (2005).

Omitted and latent variables can cause cross-sectional dependence; if company i, like company j, had more returns than explained by the model caused by the same omitted variable. Moreover, these variables can also cause time-series dependence; if company i had higher returns at time t than explained by the model caused by an omitted variable, this could also cause returns of firm i at time $t+1$ to be higher. For example, an omitted variable such as CAPEX could be serially correlated, which could cause serial correlation in the model errors even though the equity returns might show no sign of serial correlation. The next part of this subsection assesses the consistency of the FM estimator under fixed dependencies, i.e. when the errors are subject to a fixed firm effect or a fixed time effect.

To show the bias in the standard errors of the FM estimator when the errors are subject to a fixed firm effect, assume the following Data Generating Process (DGP) for the equity returns with the unobserved firm effect, γ_i. The independent variables, C, are demeaned for brevity reasons[11], C is a T by N matrix containing the $c_{i,t}$'s:

$$\begin{aligned} \varepsilon_{i,t} &= \gamma_i + \eta_{i,t} \\ r_{i,t} &= \theta c_{i,t} + \gamma_i + \eta_{i,t}. \end{aligned} \tag{3}$$

The DGP is subject to fixed unobserved heterogeneity caused by the fixed firm effect γ_i. The true unexplained part of the equity returns is denoted by $\eta_{i,t}$, following traditional error assumptions. The fixed unobserved heterogeneity complicates the estimation of the standard errors of the estimator as they are no longer uncorrelated. Assume that the DGP has cross-sectional correlated and autocorrelated independent variables, for arbitrary k assume the correlations to equal $\operatorname{corr}(C_t, C_{t-k}) = \rho_c$ and $\operatorname{corr}(C_i, C_k) = \rho_c$. The resulting data structure is presented below in an overview,

$$\begin{aligned} \operatorname{corr}(C_{i,t}, \varepsilon_{j,s}) &= 0 && \forall i,\ \forall j,\ \forall t,\ \forall s \\ \operatorname{corr}(C_{i,t}, C_{j,s}) &= 1 && \text{for } i = j \wedge t = s \\ &= \rho_c && \text{for } i = j \wedge \forall t \neq s \\ &= 0 && \forall i \neq j \\ \operatorname{corr}(\varepsilon_{it}, \varepsilon_{js}) &= \rho_c && \text{for } i = j \wedge t = s \\ &= \rho_{\varepsilon,\gamma} \ = \frac{\sigma_\gamma^2}{\sigma_\varepsilon^2} && \text{for } i = j \wedge \forall t \neq s \\ &= 0 && \text{for } \forall i \neq j \wedge t = s \\ &= 0 && \text{for } \forall i \neq j \wedge \forall t \neq s \end{aligned} \tag{4}$$

The overview shows that the residuals are correlated across firms and time. The FM regression from 2 is no longer suitable in this assumed data structure. However, the coefficient-θ estimate is still unbiased;

$$\hat{\theta}_{FM} = \theta + \frac{1}{T}\sum_{t=1}^{T}(C_t'C_t)^{-1}C_t\varepsilon_t = \theta. \tag{5}$$

The FM estimate of the coefficient is unbiased, but the coefficients' standard errors are biased in the assumed data structure. The FM approach allows the standard errors (S) to be correlated across firms, but does not account for correlation over time. The equation below derives the true variance of the estimated coefficients in the assumed data structure. One can infer the bias of the standard errors of the FM estimator from the true variance. The equation below formulates the FM-estimated squared

[11]Demeaning the independent variable can be done without loss of generality.

standard errors of the coefficient θ, $S^2(\hat{\theta}_{FM})$, and derives its true variance, $\text{Var}(\hat{\theta}_{FM})$,

$$
\begin{aligned}
S^2(\hat{\theta}_{FM}) &= \frac{1}{T}\sum_{1}^{T}\frac{(\hat{\theta}_t-\hat{\theta}_{FM})^2}{T-1} = \frac{\text{Var}(\hat{\theta}_t)}{T} = \frac{\sigma_\varepsilon^2}{NT\ \sigma_c^2} \\
\text{Var}(\hat{\theta}_{FM}) &= \text{Var}(\frac{1}{T}\sum_{t=1}^{T}\hat{\theta}_t) = \frac{1}{T}\sum_{t}^{T}\frac{\text{Var}(\hat{\theta}_t)}{T} + \frac{2\sum_{t=1}^{T-1}\sum_{t+1}^{T}\text{Cov}(\hat{\theta}_t,\hat{\theta}_s)}{T^2} \\
&= \frac{\text{Var}(\hat{\theta}_t)}{T} \quad + \frac{T(T-1)}{T^2}\ \text{Cov}\Big((C_t'C_t)^{-1}C_t'\varepsilon_t\ ,\ (C_s'C_s)^{-1}C_s'\varepsilon_s\Big) \\
&= \frac{\text{Var}(\hat{\theta}_t)}{T} \quad + \frac{T(T-1)}{T^2}\ (C_t'C_t)^{-1}C_t'\varepsilon_t\varepsilon_s'C_s(C_s'C_s)^{-1} \\
&= \frac{\text{Var}(\hat{\theta}_t)}{T} \quad + \frac{T(T-1)}{T^2}\cdot\sigma_\varepsilon^2\cdot\rho_{\varepsilon,\gamma}\cdot\frac{1}{\sigma_c^2}\cdot\rho_c \\
&= \frac{\sigma_\varepsilon^2}{NT\ \sigma_c^2}\ \big(1+(T-1)\ \rho_c\ \rho_{\varepsilon,\gamma}\big) \\
&= S^2(\hat{\theta}_{FM})\ \big(1+(T-1)\ \rho_c\ \rho_{\varepsilon,\gamma}\big)
\end{aligned} \tag{6}
$$

The equation derives the coefficient's actual variance and the coefficient's FM standard errors, which show that FM misspecifies the standard errors in the assumed data structure. The bias of the FM standard errors becomes clear from the last line of the equation, stating that the FM standard error is off by a factor of $(T-1)\rho_c\ \rho_{\varepsilon,\gamma}$. This means that the correct standard errors of the coefficient could be larger or smaller, depending on the signs of the autocorrelations of C and ε. However, one can assume both signs to be positive, as it is likely that positive (negative) errors will be followed in the next time-point by positive (negative) errors, likewise for the characteristics in C. Therefore, one can assume that both correlations are positive, such that the FM standard errors underestimate the true standard errors. The underestimated standard errors could result in wrongfully considering a coefficient to be significant.

Assume the data is subject to an unobserved fixed time effect, δ_t, instead of a fixed firm effect:

$$
\begin{aligned}
\varepsilon_{i,t} &= \delta_t + \eta_{i,t} \\
r_{i,t} &= \theta c_{i,t} + \delta_t + \eta_{i,t}.
\end{aligned} \tag{7}
$$

Assume the same data structure as in equation 4, however the error correlation structure changes for:

$$
\begin{aligned}
\text{corr}\,(\varepsilon_{it},\varepsilon_{js}) = 0 & \qquad \text{for } i=j\ \wedge\ \forall t\neq s \\
= \rho_{\varepsilon,\delta}\ = \frac{\sigma_\delta^2}{\sigma_\varepsilon^2} & \qquad \text{for } \forall i\neq j\ \wedge\ t=s
\end{aligned} \tag{8}
$$

The FM estimates are unbiased and consistent under the presented data structure with a fixed time effect, as shown in the equation below:

$$
\begin{aligned}
S^2(\hat{\theta}_{FM}) &= \frac{1}{T}\sum_{t}^{T}\frac{(\hat{\theta}_t-\hat{\theta}_{FM})^2}{T-1} = \sum_{t}^{T}\frac{\mathrm{Var}(\hat{\theta}_t)}{T^2} = \frac{\sum_t^T \sigma^2_{\varepsilon,t}}{NT^2\ \sigma^2_c} \\
\mathrm{Var}(\hat{\theta}_{FM}) &= \mathrm{Var}\big(\frac{1}{T}\sum_{t=1}^{T}\hat{\theta}_t\big) = \frac{1}{T}\sum_{t}^{T}\frac{\mathrm{Var}(\hat{\theta}_t)}{T} + \frac{2\sum_{t=1}^{T-1}\sum_{s=t+1}^{T}\mathrm{Cov}(\hat{\theta}_t,\hat{\theta}_s)}{T^2} \\
&= \ \frac{1}{T}\sum_{t}^{T}\frac{\mathrm{Var}(\hat{\theta}_t)}{T} \\
&= S^2(\hat{\theta}_{FM}).
\end{aligned} \tag{9}
$$

The above equation shows that the FM regression suits data structures subject to a fixed time effect. Thus far, the firm and time effects are assumed to be fixed, i.e. the serial dependence is constant over the firms and the cross-sectional dependence is constant over time. The following subsection does not make the assumption of fixed dependencies, but allows for time-varying unobserved heterogeneity and presents the model specification of the Group Fixed Effects (GFE) model.

5.2 Time-varying unobserved heterogeneity

This subsection presents the Group Fixed Effects (GFE) model, which does not restrict the dependencies to be fixed over one of the dimensions, i.e. over time or firms. Assume that the time effect, cross-sectional correlation, is not the same between firms but is group-specific, i.e. $\delta_t^{(g)}$, for N group firm pairs $g_i = \{1, ..., G\}^N$.[12]. The dependence structure is subject to time-varying unobserved heterogeneity, as the dependence structure is no longer fixed over one of the dimensions. Further, assume that each firm is assigned to the correct group and that the number of groups G is known. The equation below presents the assumed data structure,

$$
\begin{aligned}
\varepsilon_{i,t} &= \delta_t^g + \eta_{i,t} \\
r_{i,t} &= \theta c_{i,t} + \delta_t^g + \eta_{i,t}.
\end{aligned} \tag{10}
$$

[12]One can also assume the firm effect, i.e. unobserved heterogeneity and serial correlation, to be varying over time and not to be firm specific, but group specific.

By allowing the time effects to vary per group of firms, the FM regression no longer presents a consistent estimator. The equation below derives the estimator's variance in the assumed data-structure[13]:

$$
\begin{aligned}
S^2(\hat{\theta}_{FM}) &= \frac{1}{T}\sum_t^T \frac{(\hat{\theta}_t - \hat{\theta}_{FM})^2}{T-1} = \sum_t^T \frac{\mathrm{Var}(\hat{\theta}_t)}{T^2} = \frac{\sum_t^T \sigma^2_{\varepsilon,t}}{NT^2\ \sigma_c^2} \\
\mathrm{Var}(\hat{\theta}_{FM}) &= \mathrm{Var}(\frac{1}{T}\sum_{t=1}^T \hat{\theta}_t) = \frac{1}{T}\sum_t^T \frac{\mathrm{Var}(\hat{\theta}_t)}{T} + \frac{2\sum_{t=1}^{T-1}\sum_{s=t+1}^T \mathrm{Cov}(\hat{\theta}_t, \hat{\theta}_s)}{T^2} \\
&= \frac{1}{T^2}\sum_t^T \mathrm{Var}(\hat{\theta}_t) \qquad (11) \\
&= \frac{1}{T^2 N^2 \sigma_c^2}\sum_i^N \sum_t^T \sigma^2_{\varepsilon,t,g_i} \\
\mathrm{Var}(\hat{\theta}_{FM}) - S^2(\hat{\theta}_{FM}) &= \sum_i^N \sum_t^T \sigma^2_{\varepsilon,t,g_i} - N\sum_t^T \sigma^2_{\varepsilon,t}
\end{aligned}
$$

In the equation above $\sigma_{\varepsilon,t,g_i}$ denotes the standard deviation for firm i in group $g_i = \{1, ..., G\}^N$ at time t. From the derivation above it becomes apparent that, in general, the FM estimator is not consistent when the data is subject to time-varying unobserved heterogeneity.

However, the model in equation 2 can be adapted such that it does account for the time-varying group-specific effects. The following adapted FM specification, the GFE specification, can be applied to account for the time-varying group-specific moments,

$$r_{i,t} = a_t^{(g)} + \hat{\theta}_t c_{i,t} + e_{i,t}, \qquad (12)$$

a variation on the FM model, where instead of a_t, the model has a time-varying group intercept $a_t(g_i)$. The group intercept accounts for the time-varying unobserved heterogeneity, such that $a_t(g_i) = \delta_t^{g_i}$. As opposed to the standard FM specification, this adapted specification is able to account for the assumed dependence structure, i.e. $\mathrm{corr}(\delta_t^g, \varepsilon_{i,t}) = 0$. Furthermore, this ensures that $\sigma_{\varepsilon,t,g_i}$ equals $\sigma_{\varepsilon,t}$, such that $\mathrm{Var}(\hat{\theta}_{FM}) = S^2(\hat{\theta}_{FM})$ and the adapted FM specification provides a consistent estimator $\hat{\theta}$. The GFE specification accounts for time varying unobserved heterogeneity. However, the consistency relies on the grouping $g = 1, ...G$ with a suitable amount of groups G. The GFE estimator does not restrict the unobserved heterogeneity to be discrete, but relies on assumptions to provide a consistent estimator. The following section presents how the different types of dependencies can be detected from the data and the results of simple models. The subsections after that address the issue of partitioning the firms into groups, the estimation of the theorized estimator, the assumptions for the estimator to be asymptotically consistent and the selection of the number of groups.

5.3 Presence of error dependencies

This subsection presents the research approach to empirically assess the presence and dynamics of serial and cross-sectional dependence in the errors. Petersen (2009) suggests performing a basic pooled

[13]For simplicity in the derivation, it is assumed that the firms across groups are not subject to cross-sectional correlation and assumed that $\delta_t^{(g)}$ is not serially correlated.

OLS regression, neglecting the different time periods and firms, to investigate the standard errors. The simple regression with a single independent variable is formulated as $r_{i,t} = \alpha + \theta c_{i,t} + \varepsilon_{i,t}$, but could easily be extended to a multivariate regression. The coefficients' standard errors can be estimated in their regular form or by accounting for one of the dependencies through clustering the standard errors. In case serial (cross-sectional) dependence is present, the regular standard errors should be different from the clustered standard errors by firm (time). The regular standard errors and the clustered standard errors are estimated by;

$$\begin{aligned}
\mathrm{Var}_{(reg)}(\theta) &= \sigma^2(C'C)^{-1}, \\
\mathrm{Var}_{(cl,firms)}(\theta) &= \frac{N(NT-1)}{(NT-k)(N-1)}\Big((C'C)^{-1}\Big(\sum_{i=1}^{N} c_i' \mathrm{e}_i \mathrm{e}_i' c_i\Big)(C'C)^{-1}\Big), \\
\mathrm{Var}_{(cl,time)}(\theta) &= \frac{N(NT-1)}{(NT-k)(N-1)}\Big((C'C)^{-1}\Big(\sum_{t=1}^{T} c_t' \mathrm{e}_t \mathrm{e}_t' c_t\Big)(C'C)^{-1}\Big).
\end{aligned} \tag{13}$$

In the equation above the term $\frac{N(NT-1)}{(NT-k)(N-1)}$ denotes a finite sampling correction term for the clustered standard errors. The e_i and e_t vectors, of respective lengths T and N, are the estimated regression errors for one firm and one moment in time, i.e. serial and cross-sectional. The vector C, which is a matrix in a multivariate regression, contains the elements $c_{i,t}$. The estimation of the regular standard errors assumes that C and e are independent. Furthermore, the regular standard errors assume that C and e are individually independent across time and firms. The clustered standard errors relax this assumption for one of the dimensions, the variance clustered by firm, $\mathrm{Var}_{(cl,firms)(\theta)}$ allows for fixed serial dependence, while the variance clustered by time, $\mathrm{Var}_{(cl,time)}(\theta)$, allows for fixed cross-sectional dependence. One can assume that a fixed effect could only cause a positive correlation between the characteristics or errors over both dimensions, therefore, the regular standard errors could be equal, or less than equal to the clustered standard errors. The magnitude of the differences in the estimated standard errors are examined to empirically assess whether there is cause to account for serial and cross-sectional dependence.

The GFE estimator does not restrict the unobserved heterogeneity to be discrete. However, a firm's sector could proxy for collective sensitivities to unobservables. Therefore, the research examines the dependencies of firms within a specific sector as indicators of group-specific unobserved heterogeneity. One can establish whether there are signs of group-specific unobserved heterogeneity by comparing the within-sector error dependencies with each other and with the full sample dependencies. If the within-sector dependencies showcase (more) serial or cross-sectional dependence for specific sectors, this would indicate the presence of group-specific unobserved heterogeneity.

5.4 Accounting for time-varying unobserved heterogeneity

There are a variety of measures to cope with dependence structures that are subject to dependencies over both dimensions, e.g. δ_t and γ_i, affecting the standard errors. One could cluster the standard errors over both the firm and time dimension following Thompson (2011), or one could include dummy variables for one of the dimensions (fixed effects regression) and cluster on the other dimension as suggested by Petersen (2009). However, time-varying unobserved heterogeneity, i.e. effects dependent on both dimensions, such as δ_t^g, require a more sophisticated approach. A relatively new approach to obtain robust standard errors under is by estimating a Grouped Fixed-Effects (GFE) estimator introduced by Bonhomme and Manresa (2015). The GFE estimator clusters the data in groups and estimates a fixed effect regression to compensate for the group-specific time patterns caused by unobserved heterogeneity. By grouping the firms instead of adding fixed effects (dummies) per individual firm, one can avoid the incidental parameter bias, which may be substantial in relatively short samples Bonhomme et al. (2022). Another advantage of the GFE estimator is in its assumptions, since the GFE estimator does not assume the heterogeneity to be constant over time Bonhomme and Manresa (2015). This research builds upon the framework established by Bonhomme and Manresa (2015) and applies it to the adapted-FM model. The research employs a model closely related to Patton and Weller (2022). However, Patton and Weller (2022) allow for group-varying coefficients, opposed to this research, which allows for group-varying intercepts;

$$r_{i,t} = a_t(g_i) + \hat{\theta}_t c_{i,t} + e_{i,t}, \tag{14}$$

where $a_t(g_i)$ denotes the time-dependent intercept for each group of firms where a firm belongs to a group $g = \{1, ..., G\}$. For simplicity, the equation above is formulated with only one independent variable: c, however this research makes use of more characteristics: c_j for $j = 1, .., J$.

The 2-step GFE estimator from cite Bonhomme et al. (2022) is estimated in two steps: it classifies the individuals (in this case firms) into groups and the second step optimizes the log-likelihood function, with respect to the common parameters and group-specific parameters (θ and α). The maximization problem, conditioning on a given set of groups, is the optimization of the log-likelihood specified as:

$$\log L(\alpha, \theta) = -\frac{1}{2} \sum_t^T \sum_i^N \frac{1}{\sigma_i^2} (r_{i,t} - a_t(g_i) - \hat{\theta}_t c_{i,t})^2. \tag{15}$$

Maximizing the log-likelihood function recovers the parameters α and θ, of respective sizes: $T \times G$ and $T \times J$ parameters. The parameter α denotes the collection of the intercepts over time for each group and the parameter θ denotes the collection of the coefficients of the J characteristics over time. The first-order condition of the Log-likelihood stated below can be solved to recover the parameter values.

$$0 = \sum_{g_i - g} \frac{1}{\sigma_i^2} \begin{bmatrix} 1 \\ c'_{i,t} \end{bmatrix} \left(r_{i,t} - a_t(g_i) - \hat{\theta}_t c_{i,t} \right) \tag{16}$$

By examining the first order condition of the log-likelihood function, it becomes apparent that it presents the moment conditions of T distinct cross-sectional regressions, conditioning on the group assignments g, with precision weights $\frac{1}{\sigma_i^2}$. Following the rationale of Patton and Weller (2022), this would reduce to applying an FM regression to obtain the parameter vector α_t and the parameter θ_t for each of the T regressions.

This research applies two methods to assign the firms into groups. The first approach follows Bonhomme et al. (2022) by using the K-means algorithm, which assigns the firms based on their characteristics.

The second approach follows the approach of Patton and Weller (2022) by utilizing an Expectation Maximization (EM) algorithm, which closely resembles the K-means algorithm. This algorithm assigns firms to groups based on their in-model fit, unlike the more general K-means algorithm that does not exploit equity return dynamics for the groupings. The 2-step-GFE estimator can be estimated by performing a classification step and a maximization step. The EM-GFE estimator can be estimated by iteratively performing an estimation step and a maximization step. Both methods' maximization step is the optimization of the log-likelihood function 15, and therefore can also be optimized by estimating adapted-FM regression from equation 14. The following subsections cover the GFE estimator and its properties in more detail. Subsection 5.5 presents the group-classification step of the 2-step-GFE, based on the K-mean algorithm. Subsection 5.6 presents the expectation step and covers the Expectation-Maximization (EM) procedure. subsection 5.7 provides the asymptotic properties of the EM-GFE approach and presents under which assumptions the estimator is consistent. The last subsection 5.8 presents how the research selects the number of groups (G) for both types of GFE estimators.

5.5 The K-Means two-step Grouped Fixed Effects (KM-GFE) estimator

The K-means two-step GFE estimator, as introduced by Bonhomme and Manresa (2015), consists of two steps, the classification step and the maximization step. The classification step utilizes the K-means algorithm to cluster the data into groups. The maximization step optimizes a likelihood function conditioning on the groups provided by the classification step.

Clustering firms into groups can be done by arbitrarily classifying them on their emission intensity, size, BM ratio or ROE. However, the grouping could be performed based on multiple independent variables by employing the K-means algorithm, an unsupervised machine learning algorithm introduced by Lloyd (1982). The K-means algorithm aims to divide the data into G groups based on their characteristics. This research collects the average characteristic over the sample per firm i in the vector h_i. The vector h_i contains the sample average of the four utilized independent variables per firm: Intensity, Mcap, BM and ROE. The algorithm assigns each firm to a group such that the group's mean of the selected characteristics is closest to that of the specific firm, the equation below formulates this:

$$\left(\hat{h}(1), ..., \hat{h}(G), \hat{g}(1), ..., \hat{g}(N)\right) = \underset{\left(\tilde{h}(1),...,\tilde{h}(G),g_1,...,g_N\right)}{\arg\min} \sum_{i=1}^{N} \|h_i - \tilde{h}(g_i)\|^2. \tag{17}$$

In the equation above, g_i denotes the assignment of the N firms into G groups, $\hat{h}(g)$ is the mean of the characteristics in h_i for all firms in group g. The K-means algorithm iteratively descends to the minimum of the squared Euclidean norm of the difference between firms' characteristics to the average group characteristics. The iterative descent iterates by updating the group assignments g_i and updating the average characteristics of a group collected in $\tilde{h_i}$. Finding a global minimum that optimizes the groupings might be challenging and computationally intensive. However, a fast yet stable heuristic in the form of Lloyd's algorithm from Lloyd (1982) is applied, as this algorithm is considered a simple and reliable benchmark. After the classification step, the adapted-FM model can be estimated to obtain the K-means 2-step GFE estimator. The consistency and asymptotic properties of the K-means GFE estimator are covered in detail by Bonhomme et al. (2022), to which is referred for further details. Subsection 5.8 presents the selection of the number of groups G for the 2-step GFE estimator. The next subsections cover the EM-GFE estimator in detail with respect to groupings, estimation and asymptotic properties.

5.6 The Expectation-Maximization Grouped Fixed Effects (EM-GFE) estimator

To utilize the direct dependence information, one can classify the firms based on their error dynamics. This research proposes a GFE estimator that classifies firms based on their relative error distance. Compared to the K-means GFE estimator based on firm characteristics, this GFE estimator is more likely to cover the error dependencies. Since the groupings are based on output from the maximization step, the GFE can no longer be estimated in a 2-step approach like the K-means GFE but calls for a method that iterates between these two steps; the Expectation Maximization (EM) algorithm. The approach this research applies resembles that of Patton and Weller (2022), who also apply the EM algorithm to find group-specific parameters based on error dynamics. However, this research differs in its model specification. Patton and Weller (2022) models heterogeneous risk premia, i.e. group specific coefficients, to research whether multiple risk prices are needed in a given dataset. As opposed to Patton and Weller (2022), this research is interested in the universal effect of emission intensity on equity returns while accounting for unobserved heterogeneity, thereby utilizing the information in the dependence structure.

Per iteration of the EM algorithm the expectation step conditions on the outcome of the maximization step, the new improved model errors. Although closely related, this model requires a different optimization method than Lloyd's algorithm used for the K-means GFE. This research applies the Expectation Maximization algorithm, an iterative conditional approach, but closely related to Lloyd's algorithm, as in detail covered by Patton and Weller (2022). Maximizing the full log-likelihood over the parameters and groups at once is unsolvable, but EM poses a powerful iterative method to solve the problem. The EM algorithm starts with random groupings and iteratively updates these groupings until the EM algorithm converges. The maximization step, the estimation of the FM model with time-varying group-specific intercepts, conditions on the groupings (initial random groups or groups from the expectation step). The expectation step partitions the firms into groups, conditioning on the estimated parameters of the maximization step. The EM-GFE approach iterates between the expectation and maximization steps until convergence. Both steps are straightforward maximization problems. The expectation step builds upon the model accuracy, ignoring the intercepts α. The returns are explained by the independent variables, per point in time for each firm. The unexplained part of the equity returns of firm i are collect in h, containing N firm specific h_i vectors of length T. Each estimation step assigns the firms to the group with the greatest resemblance in unexplained equity returns. The EM-GFE model starts with the GFE classification objective from Bonhomme et al. (2022)

together with this research' specification of h_i, which is formulated below:

$$\begin{aligned}
(\hat{g_1}, ..., \hat{g_N}) = \underset{(g_1,...,g_N)}{\arg\min} \sum_{i=1}^{N} \|\hat{h_i} - \tilde{h}(g_i)\|^2. \\
\hat{h_i} = r_i - c_i \odot \hat{\theta},
\end{aligned} \tag{18}$$

The vector h_i contains the equity returns minus the characteristics multiplied (element-wise) with the coefficient, where the coefficient, $\hat{\theta}$, is obtained from the previous maximization step. The vector $\tilde{h}(g)$ contains the average $\hat{h}_i$ vector for all firms i in group $g_i = g$, with $g_i \in \{1, ..., G\}^N$. The minimization function above minimizes over all possible groupings to find the most resembling error structure for each firm. The 'most resembling error structure' is assessed through the squared Euclidean norm of the difference between the unexplained returns of firm i minus that of group g.
Considering the specification of h_i, the vector $\tilde{h_i}$ can be rewritten as $\hat{a}_g$ as shown in the following equation:

$$\tilde{h}(g) = \frac{1}{\sum_i^N I_{g_i=g}} \sum_i^N I_{g_i=g}(r_i - c_i \odot \hat{\theta}) \; = \; a(g). \tag{19}$$

From the equation above, it becomes apparent that the expectation step of the EM-GFE boils down to selecting the group g_i per firm that produces the best model fit: $\|r_i - c_i \odot \hat{\theta} - a(g)\|^2$. The algorithm can optimize the group assignments per firm, by conditioning on the parameters. The updated group assignments from the expectation step are obtained by solving the following equation per firm-i:

$$\hat{g}_i = \underset{g}{\arg\min} \sum_t^T (r_{i,t} - a_t(g) - \hat{\theta}_t c_{i,t})^2. \tag{20}$$

The maximization step boils down to selecting the group $g_i \in \{1, ..., G\}^N$ for each firm such that it reduces the total Sum of Squared Errors (SSE).
After the expectation step, one can perform the maximization step to finish one iteration of the EM algorithm. The maximization step is performed by estimating the adapted-FM model from equation 14 conditioning on the group assignments of the expectation step. The maximization step provides new parameter estimates in α and θ, which the expectation step uses.
The EM algorithm iterates over the expectation and maximization step to maximize the log-likelihood function from 15 until it converges. Since the EM-GFE model specification uses a simple regression and a simple maximization step, the EM iterates relatively fast to a minimum; it converges when the expectation step does not update the grouping of firms. As the unobserved heterogeneity is not assumed to be discrete, the GFE is able to group firms with similar sensitivities to every: latent/omitted variable, macro-economic environment and every type of shock. Therefore, the EM-GFE can provide groupings reflecting a sophisticated cross-sectional and time-series dependence structure. For this purpose, the EM-GFE poses as a parsimonious yet comprehensive model to account for unobserved heterogeneity.

5.7 Asymptotic properties of the EM-GFE estimator

Bonhomme et al. (2022) thoroughly researches the asymptotic properties of the GFE estimator. The GFE estimator's consistency relies on various assumptions regarding the groups' classification and the estimator's maximization. This subsection covers the assumptions stated in Bonhomme et al. (2022), disregarding the regularity assumptions. The regularity assumptions that this research assumes are assumptions regarding the log-likelihood to be thrice-differentiable, the second and third derivatives to be bounded away from zero, and that the true parameter values are unique and interior to the parameter spaces.

Let the $\alpha_{i,0}$ denote the true firm specific unobserved heterogeneity, which consists of T elements $\alpha_{i,t,0}$. The first assumption (A.1) states that there is a Lipschitz continuous function ϕ such that as N and T tend to infinity that:

$$\frac{1}{N}\sum_{i=1}^{N}\|h_i - \phi(\alpha_{i,0})\|^2 = O_p(1/T), \tag{21}$$

The O_p notation is the order in probability, which represents the asymptotic convergence in probability of the classifying objective. The assumption states that the true unobserved heterogeneity should asymptotically explain the moments h_i, $\alpha_{i,0}$. This means that as N and T tend to infinity that $r_i - c_i \odot \theta = \phi(\alpha_{i,0})$. This assumption should hold under the assumption that effects are estimated correctly, as then the residuals, $r_i - c_i \odot \theta$, should be explained by the unobserved heterogeneity. A second assumption (A.2) is based on injective mapping, i.e. there exists another continuous Lipschitz function ψ s.t.:

$$\alpha_{i,0} = \psi(\phi(\alpha_{i,0})) \tag{22}$$

The injective mapping assumption requires that the probability limit of h_i is explained by α_{i0} (A.1) and that the limiting probability of h_i also carries all the information in the true unobserved heterogeneity. This means that the adapted-FM model errors should contain all the information on the true unobserved heterogeneity, which should hold when the adapted-FM estimator correctly estimates the true effect. Note that the functions ϕ and ψ do not need to be known to the researcher as the true unobserved heterogeneity α_{i0} is not known either. The third (A.3) assumption that this research covers, makes assumption on the errors of the classification function, $u_i = h_i - \phi(\alpha_{i,0})$. For this assumption take r as the dimension of h_i. The following assumption is needed when accounting for time-varying unobserved heterogeneity, it requires that the tails of the errors decay strongly. More specifically, this is a necessary assumption as the time-varying GFE estimator's asymptotic properties become tougher (increasing T results in increasing r).

The assumption states that the errors should be sub-gaussian Vershynin (2018), i.e. there exists a scalar $\lambda \geq 0$ such that the following equation holds for every $\tau \in \mathbb{R}^T$:

$$\mathbb{E}\left(\exp(\tau' u_i)\right) \leq \exp(\lambda\|\tau\|^2) \tag{23}$$

This assumption requires that the tails of u_i decay strongly, as the expectation of the exponential of u_i also covers its standard deviation. Therefore, this research assumes that the errors u_i are sub-gaussian. The last assumption (A.4) requires that the ratio r/T, with r denoting the dimension of h_i, tends to a

positive constant as T tends to infinity. This assumption holds as r equals T in this research' model specification, s.t. the ratio equals 1.
This subsection presents the required assumptions for the GFE estimator to be consistent, based on the work of Bonhomme et al. (2022). It presents the required assumptions and substantiates the assumptions' validity for the EM-GFE estimator (disregarding the regularity assumptions). However, it leaves insights from the asymptotic properties of the EM-GFE estimator concerning the selection of the number of groups G to further research. The following subsection covers the selection of the number of groups G for the KM-GFE and EM-GFE.

5.8 The number of groups

In the extreme case when G equals N, i.e. when the number of groups equals the number of firms in the sample, the grouped fixed effects $\alpha_t^{(g)}$ would equal $\alpha_{i,t}$ making the independent variables $c_{i,t}$ redundant as the grouped fixed effects would perfectly estimate the returns $r_{i,t}$. The other extreme case, whit $G = 1$, would result in the regular FM estimator. The true groupings of firms are latent to the researcher, making it difficult to assess the quality of the estimated groups.
The optimal amount of groups G can be assessed by examining an elbow-plot of the WCSS (Within-Cluster Sum of Squares), resulting from equation 17 for a range of different groups G. A WCSS figure plots the performance of groupings in terms of how well equation 17 is minimized, i.e. how well the distance of the characteristics' averages of the different firms compared to that of their groups are minimized in terms of Euclidean distance. This figure plots the K-means algorithm's minimization function, representing each extra cluster's marginal improvement. In addition to assessing the elbow-plot of the WCSS, the AIC (Akaike Information Criterion) will also be considered. The AIC is a prediction error estimator which worsens as more variables are included, as opposed to in-sample errors, which benefit from more variables. The AIC takes the number of variables into account and balances that with the in-sample errors, this means that an extra variable has to contribute a certain amount of SSE-reduction to be deemed worthwhile by the AIC. This research considers an adapted version of the AIC as it only serves for model-comparison purposes, the adapted AIC considered in this research is formulated as follows;

$$\begin{aligned} A\tilde{I}C &= 2k + NT \times log(SSE) \quad \sim \quad AIC = 2k - 2\big(\log L(a, \hat{\theta})\big) \\ SSE &= \sum_t^T \sum_i^N e_{i,t}^2, \end{aligned} \tag{24}$$

As a lower AIC is preferred, the AIC punishes the number of included variables, k, and punishes the level of the SSE (Sum of Squared Errors). As more variables result in a lower SSE, the AIC balances the model's accuracy compared to the number of variables included. By punishing the number of variables, $k = T \times (G + J)$, this regularization directs the researcher to select a model with fewer groups, reducing the risk of a substantial incidental parameter bias, which occurs when many groups are included relative to individual units in the cross-section.

Pooled OLS results

Pooled OLS models:	Autocorr	Crosscorr	α (E+03)	Intensity (E+05)	Mcap (E+05)	BM (E+03)	ROE (E+05)
Regular S.E.	-0.011	0.328	11.20	-2.22	-4.41	0.49	1.62
			[1.17]	[1.31]	[0.97]	[0.70]	[2.12]
			(9.54)	(-1.69)	(-4.56)	(0.70)	(0.76)
Clustered S.E. by firm	-0.011	0.328	11.20	-2.22	-4.41	0.49	1.62
			[1.45]	[1.74]	[0.95]	[1.01]	[3.82]
			(7.71)	(-1.28)	(-4.63)	(0.48)	(0.42)
Clustered S.E. by time	-0.011	0.328	11.20	-2.22	-4.41	0.49	1.62
			[4.07]	[1.72]	[1.05]	[1.26]	[3.78]
			(2.75)	(-1.29)	(-4.19)	(0.39)	(0.43)

Table 4: This table contains the results of the pooled OLS regression with different Standard Error (S.E.) estimation methods, the model is estimated over the full sample period (2005 to 2021). The model regresses the log excess returns on: Intensity, Mcap, BM and ROE, Intensity denotes the Emission intensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization). The different standard error estimation methods for which results are reported are: regular S.E. estimation, S.E. clustered by firm and S.E. clustered by time. The table contains the coefficient estimates, the estimated standard errors (denoted between square brackets) and the t-values of the coefficients (denoted between parentheses).

6 Results

To find the effect of emission intensity on equity returns in Sweden, the research applies various models as covered in section 5. The main results of this research follow from the estimation of the *log* excess returns by the Fama Macbeth model, the KM-GFE models and the EM-GFE models, which are divided over two tables. In each model this research estimates a variation of the Fama Macbeth regression of the log excess equity returns of 77 firms on the four independent variables; emission intensity (Intensity), Market Capitalization (Mcap), Book to Market ratio (BM) and Returns On Equity (ROE) over the years 2005 to 2021. The research estimates different models to assess which model specification provides the best fit compared to its flexibility. The first subsection, 6.1, examines the dependence structure in the basic models' errors, it examines the errors at a full sample level and at a sector level. The subsection examines the presence of cross-sectional dependence and serial dependence in the different samples. The dependency dynamics show the presence of time-varying unobserved heterogeneity, which advocate the use of the GFE models. Subsection 6.2 continues by assessing the GFE specifications regarding the model fit while accounting for the models' flexibility. The last subsection, 6.3, presents the implications of the models on the effect of emission intensity on equity returns. The subsection investigates the hypothesized carbon risk premium and the other hypotheses stated in section 3.

Cross-sectional correlations within sector

Model	Health Care	Indus- trials	Finan- cials	Comm. Services	Mater- ials	Info. Tech.	Real Estate	Cons. Disc.	Cons. Stap.	Avg
Firms	6	25	11	3	6	5	8	9	3	
Pooled OLS	0.27	0.41	0.48	0.37	0.38	0.35	0.71	0.33	0.25	0.423
FM	0.07	0.01	0.05	0.17	0.05	0.09	0.30	0.04	0.31	0.081
Sector-10-GFE	-0.20	-0.04	-0.10	-0.47	-0.19	-0.24	-0.13	-0.12	-0.50	0.140
EM-2-GFE	0.03	0.01	0.04	0.20	0.05	0.11	0.24	0.04	0.22	0.071
EM-3-GFE	0.01	0.02	0.04	0.19	0.05	0.11	0.14	0.05	0.18	0.056
EM-4-GFE	0.00	-0.01	0.03	0.18	0.06	0.08	0.18	-0.01	0.13	0.050
EM-5-GFE	0.03	-0.01	0.03	0.17	0.08	-0.03	0.20	0.03	0.17	0.055
EM-6-GFE	0.02	0.01	0.03	0.19	0.07	0.06	0.07	0.03	0.21	0.044
EM-7-GFE	-0.01	0.01	0.04	0.17	0.05	0.00	0.11	0.00	0.13	0.037
EM-8-GFE	-0.02	0.00	0.04	0.03	0.04	0.03	0.10	0.04	0.19	0.036
EM-9-GFE	0.07	0.00	0.02	0.13	0.01	0.07	0.08	0.03	0.14	0.036
EM-10-GFE	0.03	-0.01	0.02	0.15	0.02	0.08	-0.01	0.03	0.18	0.034
KM-2-GFE	0.07	0.01	0.05	0.19	0.05	0.09	0.30	0.04	0.30	0.082
KM-3-GFE	0.07	0.01	0.03	0.15	0.05	0.11	0.29	0.03	0.30	0.077
KM-4-GFE	0.07	0.00	0.01	0.12	0.06	0.09	0.16	0.03	0.33	0.056
KM-5-GFE	0.06	0.00	0.01	0.13	0.04	0.07	0.16	0.03	0.31	0.053
KM-6-GFE	0.06	0.00	0.01	0.15	-0.01	0.07	0.15	0.02	0.29	0.049
KM-7-GFE	0.06	0.00	0.01	0.15	0.05	0.06	0.15	0.02	0.29	0.052
KM-8-GFE	0.06	0.00	0.02	0.11	0.05	0.06	0.15	0.01	0.29	0.050
KM-9-GFE	0.05	0.01	0.01	0.10	0.07	0.07	0.22	0.01	0.28	0.056
KM-10-GFE	0.05	0.00	0.01	0.12	0.05	0.07	0.15	0.01	0.26	0.047

Table 5: This table presents the cross sectional correlations within each sector, excluding Utilities and Energy as they, respectively, represent 0 and 1 firm(s). The table reports the number of firms in each sector underneath the sector. The table reports the cross sectional depencies for each model employed in the research; Pooled OLS, Fama Macbeth (FM) regression, Sector-10-GFE, the Expectation Maximization (EM) GFE models and the K-Means (KM) GFE models. The models are estimated over the full sample (2005-2021). The right column of the table presents the magnitude of the weighted average cross-sectional correlation over the sectors.

6.1 Error dependencies

To assess the presence of the various dependencies, the research considers the results of the Pooled OLS regressions with different standard error estimation methods as proposed by Petersen (2009). The OLS regression regresses the equity returns of the 77 firms on Intensity, the support variables and an intercept over the full sample period. Table 4 presents the results of the regression. The table reports the results of the OLS regression with regular estimated standard errors, errors clustered by firm and errors clustered by time. The coefficient θ estimates remain the same over the standard error specifications as they do not influence the coefficient estimation, as opposed to the standard errors. One can assess the presence of dependencies by comparing the standard errors between the regular estimation method and the clustered variations. For Intensity, both clustering methods report standard errors that increased by around 30% compared to the regular method. The standard errors clustered by time increased for all four variables; for BM and ROE, they increased around 80%. Furthermore, the errors have an average cross-sectional correlation of 0.33; this indicates the presence of cross-sectional dependence, which one could expect as equity prices often move in line with the equity market. The standard errors clustered by time increased around 30% for Intensity and BM, for ROE, it even increased with 80%, for Mcap, it did not increase. However, the average autocorrelation of the errors is equal to -0.011, which indicates that no time-series dependence is present in the errors. Therefore, one can exclude the presence of a time-invariant firm effect, but it indicates that endogeneity is present. The endogeneity could have various causes, among which time-varying unobserved heterogeneity, however, this needs further investigation. The OLS regression reports a negative effect of Intensity on equity returns, which is insignificant for all three standard error specifications. Although the results from the OLS regression are inconsistent, the estimated coefficients are unbiased, and therefore one could expect the effect of emission intensity on equity returns to be negative. Other models incorporating the information in the dependencies will likely pose more robust results as they rely on more information. The results from table 4 advocate the use of the FM regression or OLS with time-clustered standard errors. However, as this research is interested in the effects of emission intensity on equity returns over time, it will continue with the FM regression as a base model.

Table 5 reports the cross-sectional (error) correlations in each sector per employed model. The research groups firms into sectors as an educated guess to establish whether there is empirical evidence of unobserved heterogeneity. The educated guess stems from the assumption that firms within a sector have common sensitivities to unobserved variables and shocks. The table indicates to what degree unobserved heterogeneity is present in each model and how much information is (not) absorbed. The table shows the largest cross-sectional dependence per sector in the OLS model errors. The weighted average magnitude of cross-sectional correlation equals 0.423, after which the Sector-10-GFE model, with a magnitude of correlation equal to 0.140. [14] The FM errors show considerably less cross-sectional

[14] The Sector-10-GFE model is the only model that exclusively reports negative cross-sectional correlations within sectors. The results present negative correlations because each group (sector) has an average error equal to 0 at each point in time; in case a sector exists out of 2 firms, the cross-sectional dependence would be equal to (close to) -1, for three firms (close to) equal to -0.5, for x firms close to $-1/(x-1)$. Therefore the within-sector cross-sectional correlations do not carry any information in the GFE group specification based on sectors.

correlation within the sectors, which equals, on average, 0.081. For the FM regression, it is notable that the errors in the Real Estate, Consumer Staples and Communications Services sectors have relatively high cross-sectional correlations, regardless of the model that is employed, for FM, they respectively equal 0.30, 0.31 and 0.17. The estimated EM-10-GFE model is able to almost fully incorporate the information from the cross-sectional error correlation from the Real Estate sector, which equals -0.01, compared to the 0.30 from the FM model. This result shows the ability of the GFE models to account for unobserved heterogeneity. The EM-10-GFE reports the lowest magnitude of average cross-sectional correlation, equal to 0.034, compared to 0.081 of the FM regression. Even though the average magnitude of cross-sectional correlation has already decreased considerably compared to regular OLS dependencies, the GFE models are able to decrease this correlation further (if well specified). This research divides the sample into sectors as an educated guess of 'true' groupings. However, one can assume that other groupings with high cross-sectional dependencies exist, like the Real Estate sector, and possibly even greater. The 'actual' groupings incorporating unobserved heterogeneity are likely based on more variables and data on shocks. Therefore, the high within-sector correlations imply that the cross-sectional dependencies can be of a great magnitude for groupings based on more information than solely their sector. The GFE models are able to incorporate the group-specific cross-sectional correlation and could therefore incorporate more of the information in the dependencies and present more accurate results. The presented results indicate group-specific cross-sectional dependence and thereby advocate the use of the GFE models that account for the time-varying unobserved heterogeneity.

The research finds no notable difference between the within-sector and full-sample autocorrelations, as opposed to the within-sector cross-sectional correlations. Therefore the research refrains from presenting the results of the within-sector autocorrelations as they do not contain relevant information. As stated by Cochrane (2005), equity returns are, on average, not subject to serial dependence. Therefore, neglecting serial dependencies could be not so bad in researching equity returns. Hence, the results substantiate the claim of Cochrane (2005).

The next subsection continues by evaluating the GFE models, as those are able to account for the time-varying unobserved heterogeneity. The subsection investigates the model specifications by assessing the amount of information they are able to incorporate from the dependencies while not overfitting the model. The model that is argued to pose the best fit will be analyzed to research the effect of firms' emission intensity on their equity returns and to assess the presence of a carbon risk premium.

6.2 GFE model results

The previous section presented results on the dependence structure of the model errors. The results show that the model needs to account for cross-sectional correlation and unobserved heterogeneity. Neglecting the dependencies results in an unbiased, though inconsistent estimator of the effect of emission intensity on equity returns as covered in subsection 5.2. The GFE estimators are able to account for this dependence structure and could provide an unbiased and consistent estimator if groups are well specified. The effect of emission intensity on equity returns is likely to be influenced

Model results of full sample (2005-2021)

Model	AIC*	R^2	Autocorr	Cross-corr	$\bar{\alpha}$	$\bar{\theta}$			
						Intensity	Mcap	BM	ROE
					(E+03)	(E+05)	(E+05)	(E+03)	(E+05)
FM	1180	0.38	-0.026	-0.012	8.84	-4.20	-2.86	2.13	9.76
					(2.23)	(-1.65)	(-2.43)	(1.24)	(1.67)
Sector-10-GFE	1108	0.51	-0.038	-0.012	8.43	-7.24	-2.68	2.11	7.23
					(1.65)	(-1.95)	(-2.23)	(0.99)	(1.07)
EM-2-GFE	530	0.42	-0.035	-0.012	8.85	-3.89	-2.56	1.29	11.38
					(2.09)	(-1.54)	(-2.06)	(0.76)	(2.01)
EM-3-GFE	364	0.44	-0.034	-0.012	7.59	-3.79	-2.69	2.44	12.65
					(1.75)	(-1.43)	(-2.16)	(1.39)	(2.11)
EM-4-GFE	303	0.46	-0.037	-0.012	8.41	-3.36	-2.26	2.04	13.13
					(1.93)	(-1.29)	(-1.79)	(1.18)	(2.28)
EM-5-GFE	262	0.47	-0.038	-0.012	7.74	-3.89	-2.87	2.91	9.95
					(1.72)	(-1.63)	(-2.38)	(1.73)	(1.74)
EM-6-GFE	140	0.49	-0.039	-0.012	8.21	-5.20	-2.78	0.96	8.61
					(1.89)	(-2.02)	(-2.60)	(0.60)	(1.50)
EM-7-GFE	90	0.50	-0.039	-0.012	7.24	-5.03	-2.12	1.85	8.74
					(1.54)	(-1.93)	(-1.48)	(1.12)	(1.53)
EM-8-GFE	587	0.50	-0.038	-0.012	8.61	-5.36	-2.84	1.18	9.57
					(1.89)	(-2.04)	(-2.42)	(0.68)	(1.74)
EM-9-GFE	554	0.52	-0.033	-0.012	5.02	-2.47	-2.86	1.43	7.52
					(1.49)	(-0.89)	(-2.50)	(0.89)	(1.28)
EM-10-GFE	626	0.53	-0.037	-0.012	5.17	-1.84	-3.36	1.30	13.53
					(1.48)	(-0.69)	(-2.95)	(0.79)	(2.50)
KM-2-GFE	1239	0.39	-0.029	-0.012	-1.97	4.69	-2.92	2.20	9.56
					(0.36)	(1.11)	(-2.49)	(1.32)	(1.64)
KM-3-GFE	1332	0.40	-0.028	-0.012	4.40	4.94	-5.88	2.30	9.06
					(1.20)	(1.19)	(-3.06)	(1.36)	(1.57)
KM-4-GFE	1396	0.42	-0.029	-0.012	3.10	6.07	-4.71	2.50	8.27
					(1.11)	(1.32)	(-2.65)	(1.33)	(1.45)
KM-5-GFE	1204	0.44	-0.031	-0.012	1.56	-1.50	-4.45	2.68	3.32
					(1.06)	(-0.35)	(-2.59)	(1.42)	(0.56)
KM-6-GFE	1378	0.45	-0.031	-0.012	2.96	-1.66	-4.45	1.37	5.17
					(0.99)	(-0.39)	(-2.62)	(0.57)	(0.86)
KM-7-GFE	1509	0.46	-0.030	-0.011	2.42	1.46	-5.06	2.02	6.54
					(0.92)	(0.33)	(-2.79)	(0.83)	(1.10)
KM-8-GFE	1703	0.46	-0.029	-0.011	6.28	1.50	-8.28	3.59	5.84
					(1.28)	(0.34)	(-3.52)	(1.34)	(0.97)
KM-9-GFE	1805	0.47	-0.028	-0.011	4.75	3.80	-8.34	5.48	6.25
					(1.13)	(0.84)	(-3.51)	(1.93)	(0.97)
KM-10-GFE	1852	0.49	-0.028	-0.011	5.06	3.38	-9.08	6.43	3.74
					(1.16)	(0.73)	(-3.85)	(2.18)	(0.58)

Table 6: This table contains the results from the estimation of the log excess returns by the Fama Macbeth (FM) model, the sector GFE model, the K-means (KM) GFE models and the Expectation Maximization (EM) GFE models for the amount of groups ranging from one to ten over the full sample period (2005 to 2021). The independent variables in the models are: Intensity, Mcap, BM and ROE, Intensity denotes the Emission intensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization). Per model, the table provides the: adjusted AIC (AIC*) value, R squared, average autocorrelation, average cross-sectional correlation, average intercept ($\bar{\alpha}$), taken over all groups with its corresponding t-value and average coefficient ($\bar{\theta}$) per independent variable with its corresponding t-value. The intercept and coefficients are scaled by a factor stated underneath the variable and the t-values are denoted between parentheses underneath the average intercept and coefficient estimates.

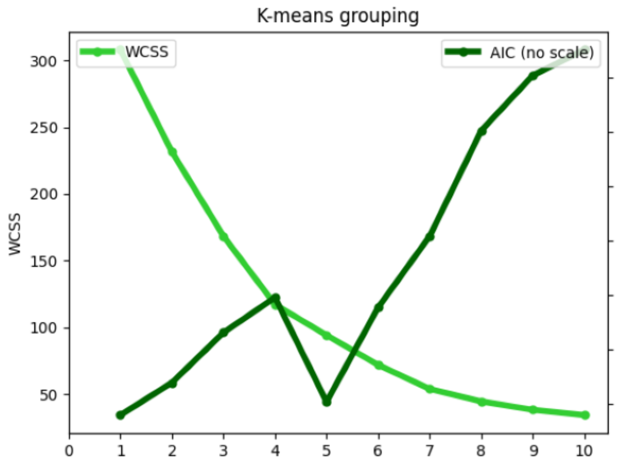

Figure 2: The K-means GFE (scaled) Akaike Information Criterion (AIC) and the Within Cluster Sum of Squares (WCSS) for the amount of groups ranging from 1 to 10. The AIC is visualized without axis as it only serves for model comparisons.

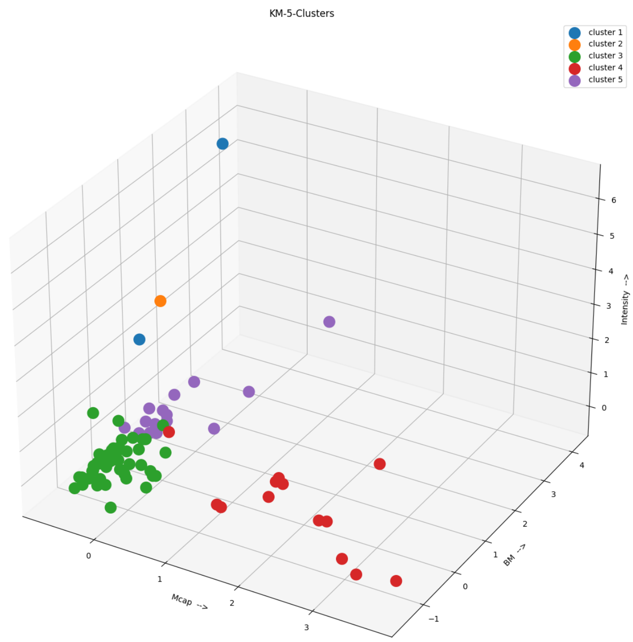

Figure 3: The groupings of the firms by the K-means 5-GFE. The x-axis denotes the Market Capitalization (Mcap) variable, the y-axis the Book to Market ratio (BM) variable and the z-axis the (emission) Intensity variable.

by things such as carbon pricing, energy prices, environmental news, sustainable innovations, firms' sustainable investments and much more. The GFE models can absorb the information embedded in the dependencies stemming from such unobservables. The groupings of the GFE estimator can be based on firm groupings from the K-means algorithm as suggested by Bonhomme and Manresa (2015). The K-means estimator relies on the information of independent variables, Intensity, Mcap, BM and ROE and uses this to form groups based on firms' relative distance to each other with respect to the variables. The firms can also be classified on their error dependencies using an EM algorithm, as introduced by Patton and Weller (2022). The EM algorithm's groups rely on the information embedded in the dynamics between the equity returns and the variables. This subsection compares the GFE models against each other and the naive groupings based on sectors (the Sector-10-GFE). The subsection studies the differences in model fit of the GFE models while accounting for their flexibility, and it evaluates the ability of each model to capture the information in the dependencies; to model the effect between emission intensity and equity returns as accurate as possible.

Table 6 presents the main results of this research. The table reports the fit of each model and presents the independent variables' average coefficients and their t-values. The models are evaluated based on their fit to the data accounting for the flexibility that each model provides. For example, the 2-GFE models are less flexible than the 10-GFE models; each additional group induces an extra intercept in each month in the sample, making the model more flexible. This research adopts the AIC (Akaike Information Criterion) to assess the model fit compared to its flexibility, i.e. its predictive accuracy. The AIC requires a certain amount of model fit improvement for extra flexibility that an additional group induces. Table 6 shows that the EM models outperform the KM models in terms of

R^2 and inherently AIC levels for each number of groups. This finding is not unexpected as the EM models, by construction, base their groupings directly on the error dependencies as opposed to the KM algorithm, which bases its groupings on the average distance between firms concerning the four independent variables. Figure 3 visualizes the groupings over the variables Mcap, BM and Intensity (respectively x,y,z axis). The figure shows that The KM algorithm clusters the groups purely based on the variables, as opposed to the EM algorithm as shown in the Appendix .... Table 7 shows the difference in groupings of the EM-2-GFE and KM-2-GFE. The table shows that the KM algorithm partitions the sample into one small group (3 firms) based on variable outliers and one large group (74 firms). The small group reports an average emission intensity equal to 187.7, compared to an average of 8.0 for the large group; there is also a clear distinction between the average values of the groups for the other variables. The difference of variable averages is naturally less for the EM groups; the EM groups, which contain 27 and 50 firms, report an average emission intensity of 14.2 and 15.4. The group differences between the EM and KM models showcase the difference in their objective functions. The best-performing KM-GFE estimator in terms of AIC (1204) is the KM-5-GFE. However, none of the KM-GFE models is able to outperform the 'best guess' grouping, the Sector-10-GFE, in terms of AIC level, nor R^2. Figure 2 shows the Within Cluster Sum of Squares (WCSS) per amount of groupings G, the WCSS line does not show a clear 'elbow' point, but the KM-4-GFE point seems like the best guess. Figure 2 also shows that the fifth group is the only additional group that resulted in an AIC decline. The drop in the AIC level of the KM-5-GFE does not correspond to a substantial decrease in WCSS, i.e. it does not correspond to an elbow point. Therefore, this research attributes this downward AIC spike to a coincidental well-fitting grouping. The KM-GFE models report varying effects of intensity on equity returns, which are all insignificant. The only models that report a negative coefficient are the KM-5-GFE and the KM-6-GFE; this inconsistency amplifies the inability of the KM groupings to account for unobserved heterogeneity.

Table 6 shows that the EM models are able to benefit in terms of AIC from additional groupings up to the EM-7-GFE, which also reports the best AIC level among all models. The EM-7-GFE reports an R^2 equal to 0.50 and reports an average effect of emission intensity on equity returns equal to $-5.03E-05$, which is significant at the 10% level (t-value equals 1.93). Table 5 reports an average cross-sectional (error) correlation over the different sectors of 0.037, which is among the lowest reported values. Table 7 reports the grouping of the EM-7-GFE model. The table shows that all firms in the financial sector, except for one, are assigned to a single group. Furthermore, the EM-7-GFE assigns the firms from the Consumer Staples and Communication Services sectors into a single group. Table 5 reports the highest cross-sectional correlation for these same sectors, which respectively equal 0.30, 0.31 and 0.17 for the errors of the FM model. The grouping indicates that the EM algorithm is a suitable method for grouping firms (or other individuals) to account for unobserved heterogeneity and benefit from the additional information within the dependence structure of the errors. The groups intend to cover firms that share the same sensitivity to unobservables. Therefore, the previous observation suggests that the 'best guess' of groups based on sectors seems like a good guess. This substantiates the approach of other studies, such as Hsu et al. (2022) and Oestreich and Tsiakas (2015), to incorporate an industry

Group statistics

Model	Health Care	Indus-trials	Finan-cials	Energy	Comm. Services	Mater-ials	Info. Tech.	Real Estate	Cons. Disc.	Cons. Stap.
Firms	6	25	11	1	3	6	5	8	9	3
EM-2-GFE										
group 1		10	5		1	4	3		4	
group 2	6	15	6	1	2	2	2	8	5	3
KM-2-GFE										
group 1		1		1		1				
group 2	6	24	11		3	5	5	8	9	3
EM-7-GFE										
group 1	1	4						7	3	
group 2		3	4			2			2	
group 3		2	2	1		2	2			
group 4	1	13	3			2	1	1		
group 5	1	1					1		1	
group 6		1					1		1	
group 7	3	1	2		3				2	3

Model	Avg. Intensity	Avg. Mcap	Avg. BM	Avg. ROE
EM-2-GFE				
group 1	14.2	72.0	0.6	7.8
group 2	15.4	43.1	0.7	8.3
KM-2-GFE				
group 1	187.7	28.1	1.8	-8.4
group 2	8.0	54.3	0.6	8.8
EM-7-GFE				
group 1	5.4	19.7	0.7	9.7
group 2	7.0	89.3	0.6	6.8
group 3	65.5	73.9	0.9	7.0
group 4	11.7	48.0	0.6	8.8
group 5	25.0	157.7	0.5	-7.1
group 6	2.3	3.7	1.0	4.2
group 7	4.0	36.4	0.7	12.3

Table 7: This table is divided into an upper and lower part, both contain information on the groupings of the EM-2-GFE, KM-2-GFE and the EM-7-GFE. The upper table contains the division of firms, classified by sector, over the groups of the models. The lower table contains the average levels of the independent variables per group over the full sample (2005-2021). The independent variables in the models are: Intensity, Mcap, BM and ROE, Intensity denotes the Emission intensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization).

factor to (partly) account for unobserved heterogeneity.

The EM-GFE models are able to account for the unobserved heterogeneity. However, table 6 shows that the average coefficient estimates are not consistent over the different amount of groups included. The Intensity coefficient of the EM-9-GFE and EM-10-GFE models decreases by more than 50% compared to the EM-8-GFE. This decrease could be caused by the great flexibility of the models or by an inaccurate grouping estimated by the EM model. The EM-8-GFE reports a coefficient for Intensity close to that of the EM-7-GFE, but already showcases an increase in the AIC level. The increase in AIC indicates that the additional group did not provide a significant increase in in-model fit. Therefore, the lower coefficients and insignificant values of the intensity coefficient could result from the 8-, 9- and 10-Group models overfitting the 'true' model. Inaccurate groupings could also cause the lower coefficients. The research estimates the EM models over 1000 random starting points, and for each additional group in the model, the amount of possible partitions of firms into groups increases exponentially. Increasing the outcome space decreases the possibility that the EM algorithm finds a global minimum, i.e. the grouping of firms that minimizes the objective function. As the unobserved heterogeneity is not likely to be discrete, grouping the firms would induce an approximation bias. The lower coefficients of the EM-9-GFE and EM-10-GFE could also be caused by an incidental parameter bias, since groupings are estimated with noise. Bonhomme et al. (2022) show that the approximation bias and incidental parameter bias affect the GFE estimator differently under different circumstances. However, further research is required to be conclusive on the cause of the different intensity coefficients of the EM-9-GFE and the EM-10-GFE. The average effect of intensity on equity returns from the EM-7-GFE model roughly indicates that an additional emission intensity of around 16.5 tonnes of emissions per MSEK revenue causes 1% annual underperformance. For the FM model, the average effect is equal to -4.2, which means that an additional emission intensity of around 20 tonne/MSEK results in 1% underperformance. To put this in perspective, the average emission intensity over the sample equals 15.0 tonne/MSEK with a standard deviation of 11.9, as covered in section 4.2. This effect seems problematic and unrealistic for Energy and Materials firms. These sectors, respectively, report an average emission intensity of 292.2 and 49.9 tonne/MSEK, which would cause these sectors to be outperformed at an annual rate of over 16% and over 2%. This relation causes substantial errors for the firms with an excessive emission intensity in the FM model due to the model misspecification. As opposed to the FM model, the GFE model can account for this endogeneity [15] by grouping firms on their level of emission intensity such that the group-specific intercept can account for this. Therefore, the GFE model is able to model a linear effect of intensity on equity returns without inducing substantial errors for the emission intensity outliers. The research chooses to linearly model the effect of intensity on equity returns because a firm's carbon costs, in essence, increase linearly with the number of its emissions[16]. Therefore, the models follow this relation more closely and better suit

[15] The endogeneity referred to is the endogeneity caused by emission intensity outliers having substantial negative errors in the FM method.

[16] In essence, this relation holds, neglecting exemptions. However, Martinsson et al. (2022) show that in parts of our sample, firms had marginal carbon tax rates different from their average rate. Furthermore, the EU ETS provides free allowances to various industries such that marginal and average costs per emission are not necessarily the same.

the goal of this research; how does carbon pricing affect the effect of intensity on equity returns? The next subsection aims to translate and explain the models' results (primarily of the EM-7-GFE) concerning a carbon risk premium and to what degree carbon pricing could have affected the model results.

6.3 Carbon risk realizations

As suggested by the EM-7-GFE model, the model of choice, the average negative effect of intensity on equity returns caused emission-intense firms to have had fewer equity returns over the years from 2005 to 2021 on the Swedish equity markets. The negative effect of emission intensity on equity returns contrasts that of Bolton and Kacperczyk (2021) and Hsu et al. (2022), who in the U.S., respectively, find no significant effect and a positive effect from emission intensity on equity returns. The different interpretation of emission intensity is notable as Hsu et al. (2022) determines it as the ratio of toxic emissions over a firm's total assets. Hsu et al. (2022) finds that emission-intense firms have higher risk premia connected to a regulation regime shift into a stringent regulation. By regarding (relatively) high carbon prices as 'stringent carbon regulation', this research states that Sweden has evolved over the years into one of the most stringent countries in terms of carbon regulation. The carbon risk following the interpretation of Hsu et al. (2022) has, for a certain amount, been realized into actual carbon prices. The carbon risk premium caused by the risk of more stringent regulation, therefore, affects countries where there has been no or a low carbon price more than countries where the regulation increased over time, which diminishes the premium. Therefore, the result of not finding a positive relation of emission intensity on equity returns can be explained by the result from Hsu et al. (2022) that emission-intense firms have higher risk premia connected to a regulation regime shift into a stringent regulation.
As hypothesized in section 3 the carbon (pricing) risk premium is based on the expected future carbon price compared to the current price. The research assumes that the expected future carbon price exceeds the current price over the entire sample. The carbon risk premium can increase, stay the same or diminish at each point in time in the sample depending on the circumstances. For a risk premium to increase (decrease), the equity subject to it has to decrease (increase) in value. As it is impossible to determine the size of a risk premium, this research pays great interest to the following events that are likely to affect the risk premium: the start of EU ETS Phase 3, periods of price increases of the EU ETS and carbon tax rate changes. This subsection examines figure 4, with special attention to the mentioned events, to empirically assess whether the hypotheses covered in section 3 can be substantiated.

Figure 4 shows the coefficient of Intensity over time for the FM regression, the EM-7-GFE estimator and the KM-5-GFE estimators. The figure also shows the changes in the Swedish carbon tax rate and the EU ETS allowance price; vertical lines represent points in time where one of the covered events commenced/ended. This section focuses on the sub-figure containing the EM-7-GFE, which is considered this research's main model [17]. The figure shows that the past-year average effect alters in sign over time, indicating that the carbon risk premium changed over time. The vertical lines represent

[17] Although the sub-figure with the coefficient from the FM regression is much like the sub-figure of the EM-7-GFE.

Intensity coefficient over time with carbon price changes

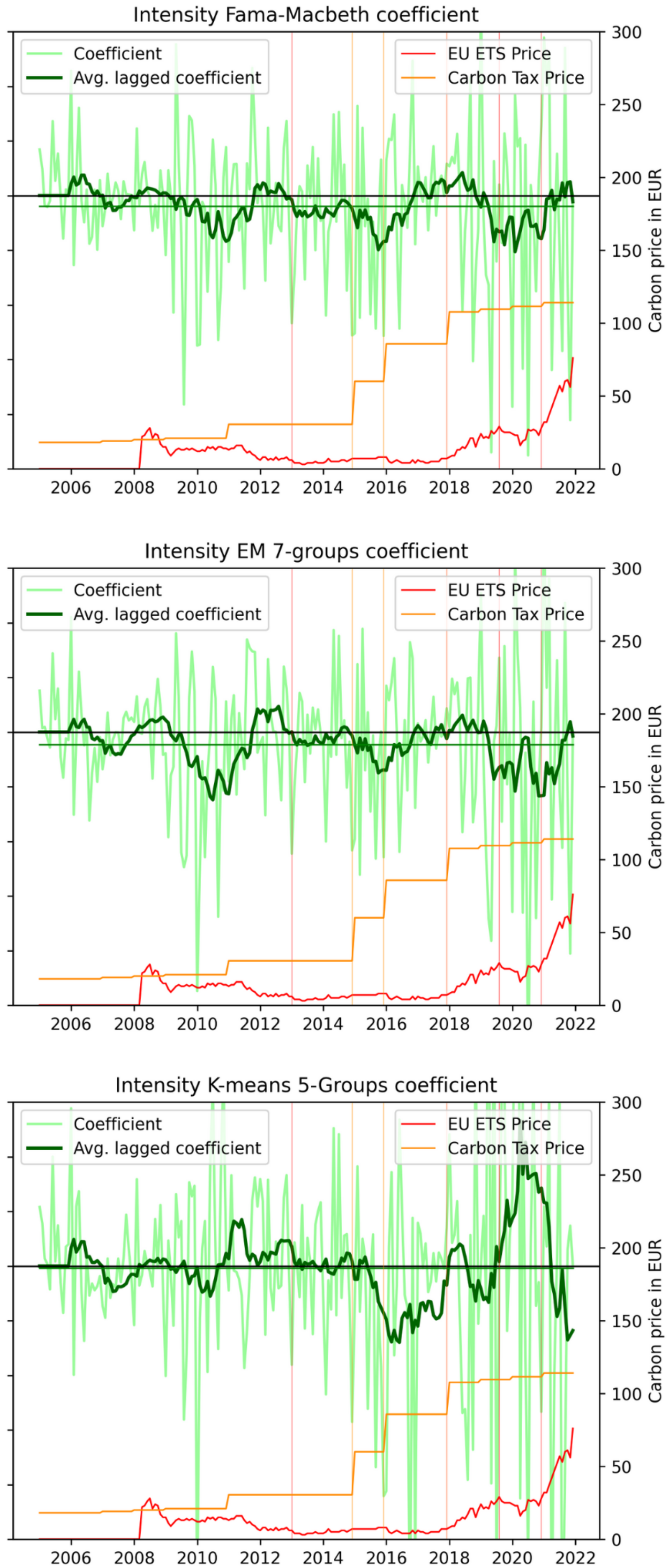

Figure 4: Three figures presenting the estimated emission intensity coefficient over time for the Fama-Macbeth regression, the EM-7-GFE estimator and the KM-5-GFE estimator. The light-green line represents the monthly coefficient and the dark-green line represents the average past-year coefficient. The lower part of each figure contains the carbon price over time for the EU ETS and the Swedish manufacturing carbon tax rate. The vertical lines correspond to: the start of a new EU ETS phase, a carbon price increase, the start of carbon price increases or the end of carbon price increases. The coefficients are estimated over the full sample (2005 to 2021).

Intensity effect on EPS, before- and after tax, over time

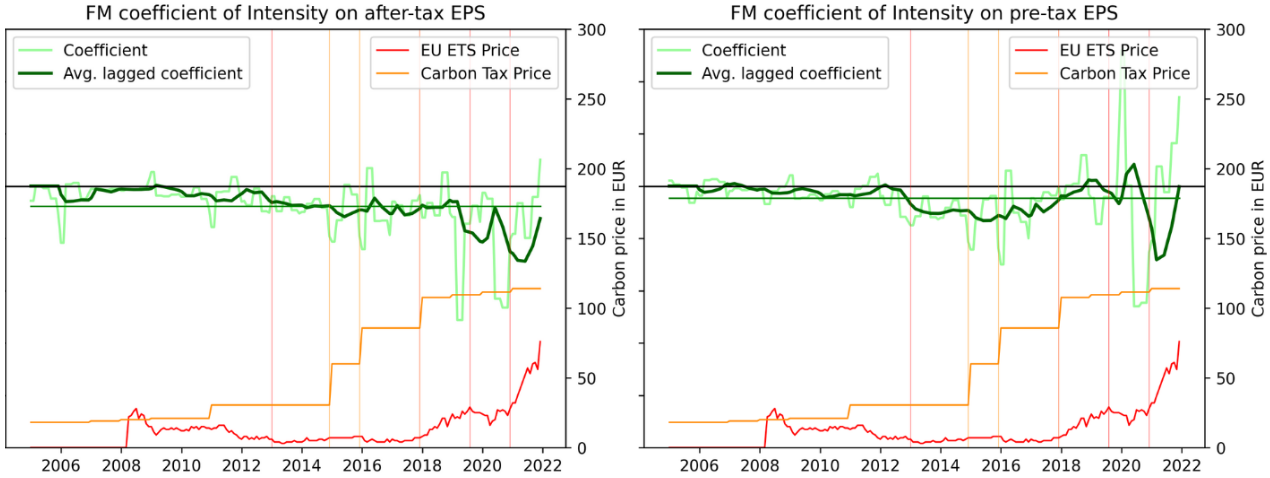

Figure 5: Two figures presenting the effect of a firm's emission intensity on its earnings over time. The Fama-Macbeth coefficients are estimated for emission intensity on: after tax Earnings Per Share (EPS) in the left figure and on before tax EPS in the right figure. The light-green lines represent the monthly coefficients and the dark-green lines represent the average past-year coefficient. The lower part of each figure contains the carbon price over time for the EU ETS and the Swedish manufacturing carbon tax rate. The vertical lines correspond: The start of a new EU ETS phase, to a carbon price increase, the start of carbon price increases or the end of carbon price increases. The coefficients are estimated over the full sample from 2005 to 2021.

the following events: The start of EU ETS phase 3 (2013), roughly doubling of the manufacturing carbon tax rate (2015), a great carbon tax rate increase (2016), another big carbon tax rate increase (2018), The start of increasing allowance prices (2018), the start of a dip in allowance prices (August 2019), end of the allowance price dip (December 2020), the start of EU ETS phase 4 (2021). From 2015 to 2018, the manufacturing carbon tax rate increased with three big tax increases. During this period, the average past-year intensity effect has mostly been negative. Over the period from 2018 to 2021, when the allowance price increased from €8 to €76, the average past-year effect has mostly been negative as well. The two windows of price increases with an overall strong negative past-year effect indicate that non-intense firms faced windfall equity returns over these periods. Notable is the allowance price dip (end of 2021) which coincides with increments of the average past-year effect as well. As opposed to the previous observations, the steep increase in allowance prices in 2021 did not coincide with a strong past-year negative effect. In 2020 the Covid-19 pandemic emerged and likely affected the intensity effect on equity returns. Therefore, the contradicting observation could have been caused by turbulent markets. Still, this finding weakens the claim that periods of increasing carbon prices are favourable to non-intense equity. The EM-7-GFE model is estimated from 2013-2021 to assess the overall effect of the period that saw the most carbon price increases. However, Appendix table 10 shows the results of the models over the period 2013-2021, which starts at the start of EU ETS phase 3. The table reports an average effect of intensity on equity returns of $-8.01\text{E}{-05}$ for the EM-7-GFE model. Hence, the effect between 2013-2021 is larger than the effect over the full sample from 2005-2021, $-5.03\text{E}{-05}$. The years from 2005-2013, which the subsample ignores, cover fewer and smaller carbon price increases than the subsample. Therefore, the finding of a larger effect of intensity in the subsample supports the claim that risk realizations (carbon price increases) favour non-intense firms. Appendix table 12 shows that the average costs of the carbon tax over the sectors

(NACE denoted) vary over the sample between 0.13% and 0.25% of their net turnover. Two sectors, Agriculture, Forestry and Fishing and Mining and Quarrying, reportedly paid over 1% of their net turnover to the carbon tax in some years. 3 hypothesized that the carbon risk premium would diminish with carbon price realizations as carbon pricing affect firms' earnings. Figure 5 shows the effects of emission intensity on the EPS after tax and the EPS before tax estimated with a simple FM regression. These figures show that the effect of intensity on earnings increased over time. The figures show that the effect of intensity on EPS after tax has, on average, a greater effect than on EPS before tax. These findings support the hypothesized effects of Blitz and Hoogteijling (2022), who assumed that carbon pricing would negatively affect valuation metrics such as EPS. Blitz and Hoogteijling (2022) theorizes that a carbon tax of $100 would result in a 50% carbon footprint reduction of a value-portfolio. This research is not able to verify this effect as the dynamics between the intertwined EU ETS and carbon tax do not put a single price on emissions. However, this research shows that the increasing carbon prices increasingly affect the EPS valuation metric. Appendix table 9 reports the regression results, which report a highly significant effect of $-5.71E-03$ and $-3.74E-03$ of emission intensity on respectively EPS after tax and EPS pre-tax. This result shows that carbon pricing influences earnings and, thereby, the Return On Equity (ROE). The effect of intensity on EPS suggests that the carbon price increases transfer carbon risk into lower ROE values, i.e. carbon (pricing) risk realizations. Carbon risk realizations diminish the carbon (pricing) risk and lower the Return On Equity (ROE). A lower ROE causes lower equity returns and lower risk causes lower equity returns as well. These effects are stronger for emission-intense firms, i.e. risk realizations have a greater negative effect on the equity returns of emission-intense firms. This stronger effect on emission-intense firms substantiates the result of an average negative effect of emission intensity on equity returns in Sweden, as Sweden has experienced several of these risk realizations. Notable is the counter-intuitive effect at the end of the sample, where the EU ETS allowance price hiked and the effect of intensity on EPS diminished. Figure 4 and 5 show a counter-intuitive effect in the second half of 2021; these phenomena could be assumed to be related to the strong increase in energy prices which occurred in that same period. However, this is left for further research to investigate.

It is hard and maybe even impossible to investigate the true dynamics of a carbon (pricing) risk premium with limited data on emissions and a complex effective carbon price. However, the results presented in this section contribute to the understanding of a carbon risk premium and provide modest substantiation of the hypotheses from 3. The hypotheses suggest that the effect of intensity on equity returns relies on carbon pricing conditions. The results of Hsu et al. (2022) and Bolton and Kacperczyk (2021) are based on U.S. equity markets with few carbon pricing changes compared to Sweden[18]. Therefore, this research attributes its finding of a negative effect of emission intensity on equity returns to the carbon price, which gradually increased over the sample.

[18]The U.S. only prices carbon in a few states, which have prices that are considerably lower than in Sweden. California currently has the highest carbon price in the U.S., which is below 30€

7 Conclusion

This research presents a new method that accounts for time-varying unobserved heterogeneity in asset pricing research, the EM-GFE. The new method unites the Grouped Fixed-Effects (GFE) framework from Bonhomme et al. (2022) with the approach of classifying firms into groups of Patton and Weller (2022). The GFE models are estimated to research the effect of emission intensity (emissions per revenue) on equity returns. The EM-GFE estimator does not restrict the heterogeneity to be discrete, as opposed to other studies into the emission intensity effect, such as Bolton and Kacperczyk (2021) and Hsu et al. (2022), who use industry fixed effects. The research focuses on the Swedish equity market over the sample period of 2005-2021. The companies in Sweden are subject to the EU ETS and the Swedish carbon tax. The EU ETS saw great price increases over the past years. The carbon tax gradually increased from its implementation in 1991 to the highest carbon tax that is currently imposed. Therefore, this study researches the Swedish equity market as it faced numerous carbon price increases over the sample period. The research shows that cross-sectional dependence is present over the full cross-section of firms but is even stronger within sectors. This result indicates that the regular Fama-Macbeth regression from Fama and MacBeth (1973) no longer presents a consistent estimator. This result motivates this research to model cross-sectional dependence per group. The employed models for this purpose are the Expectation Maximization (EM) GFE and the K-means (KM) GFE. The KM-GFE classifies firms on their relative characteristic distances. The EM-GFE classifies groups on their error dependence and iteratively optimizes the groupings and model parameters. The KM-GFE did not seem to be able to account for the unobserved heterogeneity in the specific model specification, as opposed to the EM-GFE. The groups of the EM-GFE are in line with the insights from the within-sector cross-sectional correlations. For example, the EM-7-GFE estimated groups that put sectors with high cross-sectional correlations into a single group. The grouping of the EM-GFE model shows the competence of the EM-GFE estimator to account for the time-varying unobserved heterogeneity.

The EM-7-GFE, the model of choice, finds a negative effect of emission intensity at a significance level of 10%. The model estimates an average effect of intensity on equity returns of $-5.03E-05$, which roughly indicates that an additional emission intensity of 16.5 tonne/MSEK corresponds to an annual equity-return under-performance of 1%. The research estimates a simple Fama Macbeth regression to estimate the effect of emission intensity on earnings per share (EPS) before tax and on EPS after tax. This research finds a significant negative effect of emission intensity on firms' EPS, which grows over the sample. Furthermore, the effect of emission intensity on earnings after tax is more pronounced than on earnings before tax. This difference highlights the influence of the carbon tax on the effect of emission intensity on earnings.

Hsu et al. (2022) find that the risk of future stringent regulation can explain carbon risk; this research interprets stringent regulation as a high price on carbon. Therefore, following this interpretation, the carbon risk realizes as the carbon price increases. This research states that the carbon (pricing) risk realizations transfer the risk to lower earnings values since emission intensity increasingly affects EPS over the sample. The research empirically investigates the realizations of carbon risk, which suggests

that carbon risk realizations cause non-intense firms to outperform intense firms regarding equity returns, in line with the statement.
The main finding of this research is the negative effect of emission intensity on equity returns, which is opposite to the effect found by Hsu et al. (2022) and Bolton and Kacperczyk (2021) who research the U.S. market. The research can not be conclusive on the underlying of this finding. However, based on its findings, this study argues that the realizations of carbon (pricing) risk, i.e. carbon price increases, cause the negative effect. It argues that the risk realizations diminish the risk on emission-intense firms, which lowers their equity returns. Furthermore, it argues that the risk realizations diminish the earnings of emission-intense firms and, through their ROE, lower their equity returns. Therefore, this research attributes its finding of a negative effect of emission intensity on equity returns to the numerous carbon risk realizations that Sweden faced during the period from 2005-2021.

This research adds to the literature of discretizing unobserved heterogeneity by estimating a GFE estimator using the EM algorithm. It adds to the the literature of risk-price estimation by applying a new method that accounts for unobserved heterogeneity. Furthermore, this study adds to the literature of the asset pricing consequences of increasing environmental legislation stringency by researching the dynamics of a carbon (pricing) risk premium in an unique market setting that experienced numerous, considerable carbon price increases.
Further research comparing the effects of emission intensity on equity returns in various countries with different levels of carbon pricing could benefit the understanding of a carbon risk premium. This research does not consider energy prices. However, energy prices are likely to influence the effect of emission intensity on equity returns; this leaves room for further research. Further research into the asymptotic properties of the EM-GFE estimator and the selection of the number of groups, based on the parameter and approximation bias as covered in Bonhomme et al. (2022), could benefit the model estimation.

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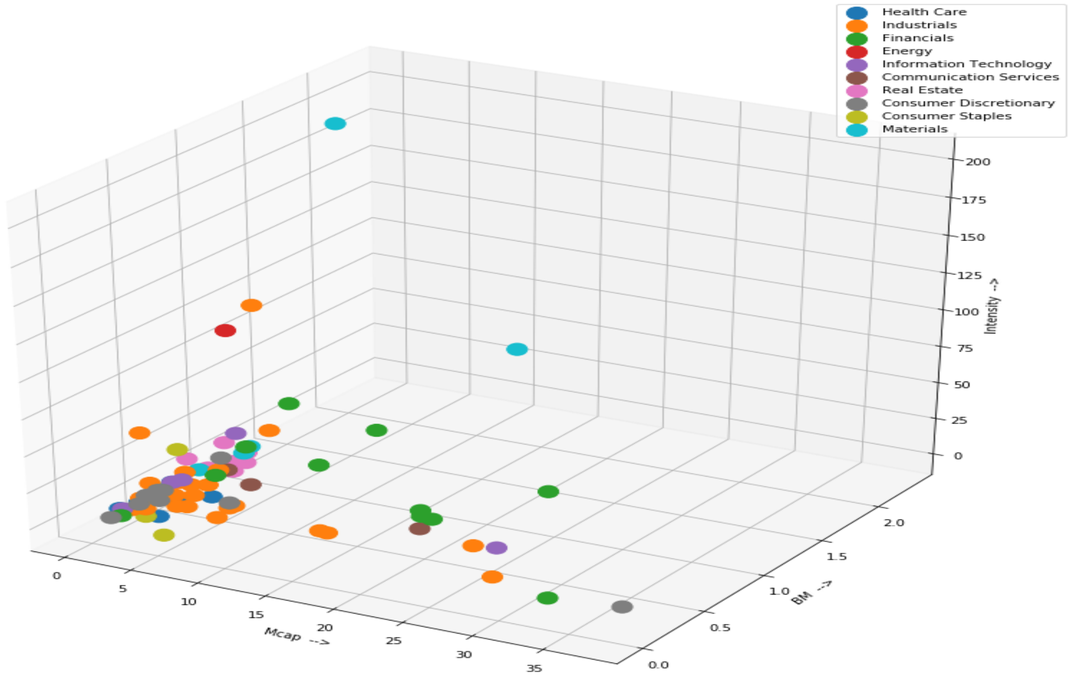
A Appendix

A.1 Descriptive data figures



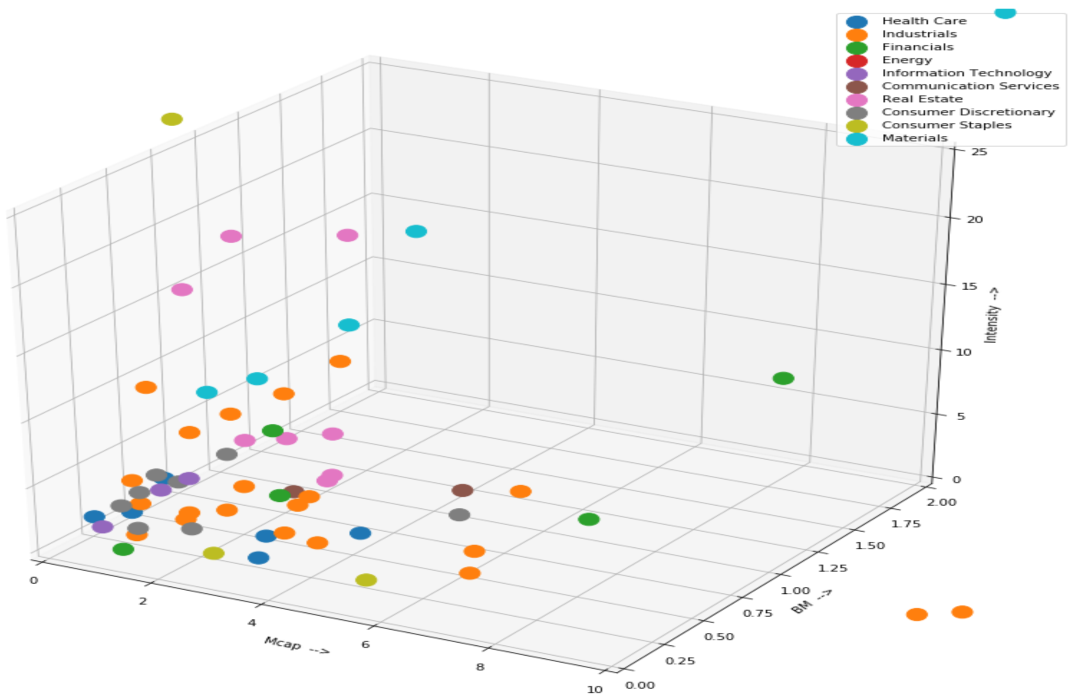


Figure 6: Figures showing the dispersion of firms classified by sector. In the figures the firms are characterized by the average, between 2010 and 2020, market capitalization in EUR billions (Mcap), their Book to Market ratio (BM) and their emission intensity, expressed in tonnes per million SEK. The top figure is the full scope over the metrics, the bottom figure is zoomed in on the cluster.

Descriptive statistics per sector

	Mean	St. dev	Minimum	Maximum	Cross-corr	Autocorr
			6 Firms:	**Health Care**		
Intensity	1.8	1.4	0.0	8.9	0.53	0.48
Mcap	17.2	10.6	0.1	107.6	0.72	0.96
BM	0.4	0.2	0.0	2.6	0.17	0.96
ROE	3.1	13.9	-339.0	146.0	-0.08	0.65
			25 Firms:	**Industrials**		
Intensity	10.9	9.2	0.0	446.4	0.27	0.44
Mcap	48.8	24.8	0.2	733.0	0.68	0.96
BM	0.5	0.3	-1.0	19.4	0.43	0.91
ROE	4.9	12.5	-1138.5	137.1	0.12	0.75
			11 Firms:	**Financials**		
Intensity	6.5	5.3	-0.3	125.6	0.14	0.28
Mcap	107.8	44.2	0.6	712.4	0.52	0.97
BM	1.0	0.5	0.1	26.5	0.19	0.87
ROE	15.6	48.5	-221.2	2607.4	0.09	0.70
			1 Firm:	**Energy**		
Intensity	292.2	309.1	18.3	1145.6		0.79
Mcap	45.0	25.6	11.0	115.8		0.97
BM	2.8	7.9	-2.0	51.3		0.88
ROE	10.1	115.6	-587.1	616.6		0.68
			3 Firms:	**Communication Services**		
Intensity	2.2	1.4	0.2	8.5	-0.11	0.57
Mcap	88.9	19.4	5.1	281.7	0.04	0.95
BM	0.8	0.4	0.3	3.5	0.52	0.94
ROE	14.1	51.3	-169.5	958.6	0.01	0.68
			6 Firms:	**Materials**		
Intensity	49.9	25.8	4.1	295.1	0.31	0.59
Mcap	38.0	19.2	0.4	215.5	0.41	0.97
BM	1.2	0.7	0.2	7.9	0.38	0.95
ROE	13.1	33.8	-94.4	1246.7	-0.06	0.70

	Mean	St. dev	Minimum	Maximum	Cross-corr	Autocorr
			5 Firms:	**Information Technology**		
Intensity	14.5	10.7	0.1	203.2	0.69	0.47
Mcap	77.7	34.8	0.2	477.4	0.63	0.96
BM	0.4	0.3	0.0	5.0	0.69	0.95
ROE	3.6	9.8	-82.1	188.7	0.21	0.70
			8 Firms	**Real Estate**		
Intensity	9.2	6.0	0.5	35.2	0.12	0.61
Mcap	15.9	11.7	0.0	126.3	0.90	0.96
BM	0.9	0.3	0.2	4.0	0.61	0.90
ROE	12.0	17.0	-225.6	105.5	0.53	0.72
			9 Firms:	**Consumer Discretionary**		
Intensity	2.7	1.1	0.2	10.9	0.79	0.71
Mcap	50.4	15.0	0.4	602.1	0.36	0.95
BM	0.4	0.2	0.0	4.5	0.20	0.93
ROE	5.6	7.5	-64.4	66.4	0.03	0.65
			3 Firms:	**Consumer Staples**		
Intensity	10.5	12.5	0.2	103.3	0.29	0.48
Mcap	27.6	13.2	0.6	125.9	0.73	0.98
BM	0.3	0.1	-0.1	1.3	0.63	0.95
ROE	5.1	3.9	-21.0	18.5	0.13	0.74

Table 8: Descriptive statistics per sector over the full sample (2005-2021). Per sector that this research considers; Health Care, Industrials, Financials, Energy, Communication Services, Materials, Information Technology, Real Estate, Consumer Discretionary and Consumer Staples are various statistics denoted. The mean, standard deviation (St. dev), minimum, maximum, average cross sectional correlation (Cross-corr) and average autocorrelation are displayed for the four variables of interest in this research. Intensity denotes the Emission inntensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization).

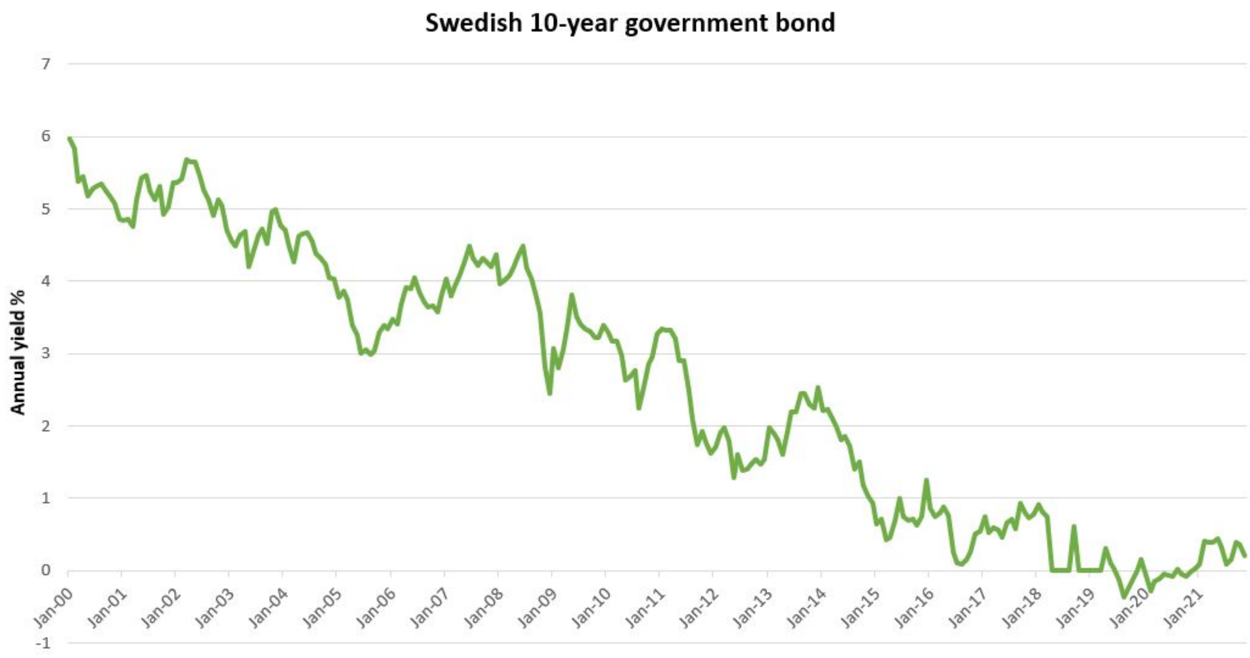


Figure 7: The annualized yield of the Swedish 10-year government bond over time from 2000 to 2021.

A.2 Additional results

Results of FM regressions of EPS on emission intensity

Dependent Variable	AIC	R^2	Autocorr	Cross-corr	α	θ (E+03)
EPS pre tax	4503	0.13	0.76	0.22	1.85	-3.74
					(24.1)	(-5.0)
EPS after tax	17185	0.07	0.74	0.27	1.85	-5.71
					(18.9)	(-8.7)

Table 9: This table presents the results of the two regression of Earnings Per Share (EPS) on emission intensity. The first regression takes EPS pre tax as dependent variable, the second regression takes EPS after tax as dependent variable. In this table α denotes the intercept and θ denotes the coefficient (which is scaled by $E + 03$). The t-values of the parameters are denoted between parentheses. The models are estimated over the full sample from 2005-2021.

Model results of sub-sample (2013-2021)

Model	AIC*	R^2	Autocorr	Cross-corr	$\bar{\alpha}$	$\bar{\theta}$			
						Intensity	Mcap	BM	ROE
					(E+03)	(E+05)	(E+05)	(E+03)	(E+05)
FM	820	0.38	-0.033	-0.012	15.35	-6.52	-3.68	1.91	8.26
					(2.84)	(-1.50)	(-3.09)	(0.69)	(1.09)
EM-2-GFE	734	0.40	-0.036	-0.012	14.86	-6.44	-3.44	1.57	8.54
					(2.58)	(-1.49)	(-2.82)	(0.56)	(1.14)
EM-3-GFE	693	0.42	-0.038	-0.012	13.83	-5.63	-3.31	2.78	7.94
					(2.37)	(-1.23)	(-2.68)	(0.98)	(1.05)
EM-4-GFE	622	0.44	-0.036	-0.012	13.86	-5.48	-3.12	3.29	11.09
					(2.31)	(-1.22)	(-2.48)	(1.14)	(1.50)
EM-5-GFE	605	0.45	-0.041	-0.012	14.19	-5.50	-3.73	3.85	7.61
					(2.27)	(-1.35)	(-2.97)	(1.39)	(1.01)
EM-6-GFE	347	0.48	-0.039	-0.012	14.41	-8.87	-2.60	1.30	5.89
					(2.35)	(-2.04)	(-2.49)	(0.50)	(0.78)
EM-7-GFE	574	0.48	-0.046	-0.012	14.91	-6.92	-3.93	1.74	5.52
					(2.21)	(-1.58)	(-2.96)	(0.65)	(0.79)
EM-8-GFE	592	0.49	-0.038	-0.012	15.64	-8.02	-3.30	1.19	9.43
					(2.36)	(-1.81)	(-2.79)	(0.42)	(1.38)
EM-9-GFE	615	0.51	-0.034	-0.012	13.47	-6.17	-3.31	1.36	2.81
					(2.16)	(-1.32)	(-2.84)	(0.52)	(0.40)
EM-10-GFE	671	0.52	-0.041	-0.012	11.83	-3.02	-3.86	1.74	9.86
					(2.03)	(-0.65)	(-3.16)	(0.64)	(1.41)
KM-2-GFE	845	0.39	-0.035	-0.012	7.59	2.49	-3.76	1.84	8.34
					(1.40)	(0.32)	(-3.19)	(0.68)	(1.16)
KM-3-GFE	927	0.40	-0.033	-0.012	12.45	3.33	-6.74	2.07	8.20
					(1.89)	(0.43)	(-2.97)	(0.75)	(1.13)
KM-4-GFE	929	0.42	-0.035	-0.012	9.72	5.09	-5.39	1.72	7.50
					(1.83)	(0.59)	(-2.58)	(0.55)	(1.05)
KM-5-GFE	762	0.44	-0.038	-0.012	10.72	-5.71	-4.66	1.70	-1.32
					(1.78)	(-0.71)	(-2.35)	(0.54)	(-0.18)
KM-6-GFE	870	0.45	-0.038	-0.011	11.89	-6.21	-4.94	-0.21	0.66
					(1.59)	(-0.79)	(-2.54)	(-0.06)	(0.09)
KM-7-GFE	988	0.46	-0.036	-0.011	8.56	1.32	-6.27	0.57	3.81
					(1.41)	(0.17)	(-2.76)	(0.15)	(0.51)
KM-8-GFE	1050	0.47	-0.035	-0.011	13.18	1.55	-9.57	3.06	4.12
					(1.62)	(0.20)	(-2.87)	(0.72)	(0.55)
KM-9-GFE	1142	0.47	-0.036	-0.011	10.36	5.51	-9.53	5.53	4.74
					(1.43)	(0.70)	(-2.83)	(1.17)	(0.59)
KM-10-GFE	1077	0.49	-0.036	-0.011	11.89	4.77	-10.75	6.36	2.77
					(1.52)	(0.59)	(-3.17)	(1.31)	(0.33)

Table 10: This table contains results from the estimation of the log excess returns by the Fama Macbeth (FM) model, the sector GFE model, the K-means (KM) GFE models and the Expectation Maximization (EM) GFE models for the amount of groups ranging from one to ten over the sub-sample period from 2013 to 2021. The independent variables in the models are: Intensity, Mcap, BM and ROE, Intensity denotes the Emission intensity, i.e. emission per revenue (in tonnes per million SEK), Mcap denotes the Market Capitalization (in billion SEK), BM denotes the Book to Market ratio, and ROE are the returns on equity (percentage of earnings per market capitalization). Per model, the table provides the: adjusted AIC (AIC*) value, R squared, average autocorrelation, average cross-sectional correlation, average intercept ($\bar{\alpha}$) taken over all groups with its corresponding t-value and average coefficient ($\bar{\theta}$) per independent variable with its corresponding t-value. The intercept and coefficients are scaled by a factor stated underneath the variable and the t-values are denoted between parentheses underneath the average intercept and coefficient estimates.

A.3 Visualization of group estimates

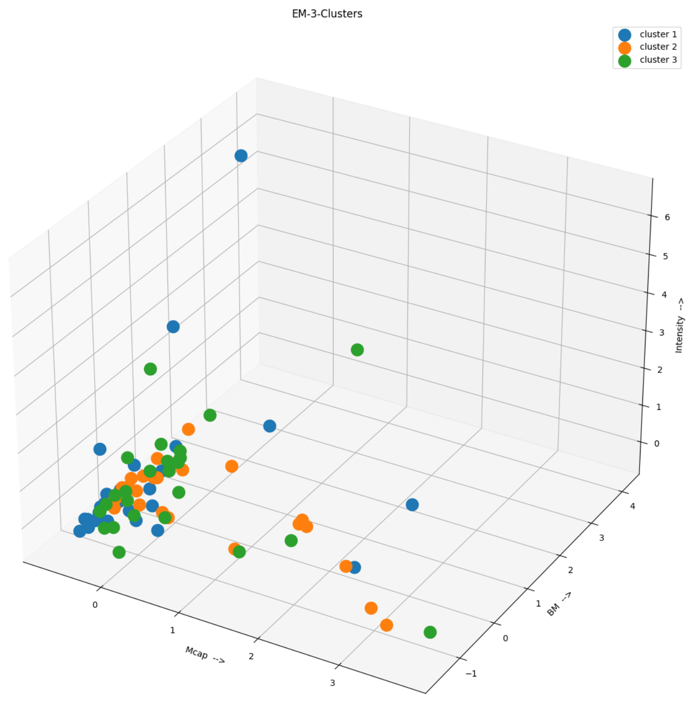


Figure 8: The groupings of the firms by the EM 3-GFE. The x-axis denotes the Market Capitalization (Mcap) variable, the y-axis the Book to Market ratio (BM) variable and the z-axis the (emission) intensity variable.

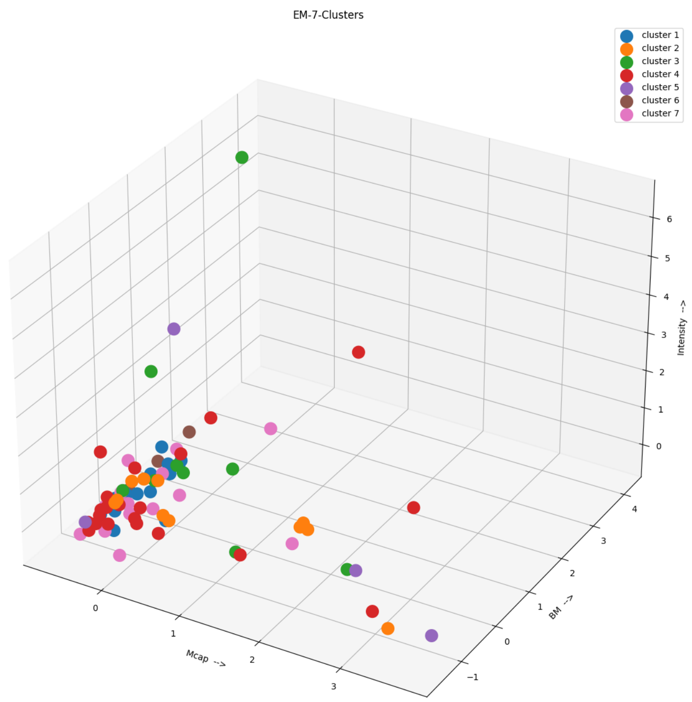


Figure 9: The groupings of the firms by the EM 7-GFE. The x-axis denotes the Market Capitalization (Mcap) variable, the y-axis the Book to Market ratio (BM) variable and the z-axis the (emission) intensity variable.

A.4 SCB data

Average tax rate paid per tonne of emissions

Average Carbon Price (in eur per tonne)	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A - Agriculture, forestry and fishing	48	52	51	56	59	64	65	83	72	72	70	62
B - Mining and quarrying	16	17	16	15	16	16	18	32	42	43	46	44
C - Manufacturing	10	12	10	10	11	10	11	11	13	14	15	15
D - Electricity, gas, steam and air conditioning supply	3	4	5	4	5	4	5	5	8	6	10	12
E - Water supply; sewerage; waste managment and remediation activities	60	62	67	63	61	58	58	60	59	56	54	51
F - Construction	100	106	109	102	108	105	103	105	107	108	102	94
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	95	102	103	98	104	98	102	105	106	107	102	99
H - Transporting and storage	36	37	40	45	45	38	34	28	24	26	25	24
I - Accommodation and food service activities	98	103	106	102	108	106	104	107	108	108	105	102
J - Information and communication	99	103	106	102	108	106	105	107	108	109	106	103
K - Financial and insurance activities	100	105	108	104	111	108	107	109	110	111	105	100
L - Real estate activities	97	103	106	98	105	103	101	104	105	106	106	107
M-Education	99	104	106	102	108	106	105	107	108	109	105	101
N-Health and social work	98	104	107	101	107	97	103	107	107	109	104	97
O-Other community, social and personal service activities												
P-Private household with employed persons												
Q-Extra -territorial organziations and bodies												
tot-Total	29	32	31	32	34	32	32	32	32	32	32	32

Table 11: The average carbon price each sector pays to the Swedish government over the period 2008 to 2019. Green cells indicate that a sector pays on average a relatively small amount for its emissions compared to others.

Carbon tax percentage of net turnover

Carbon Tax % of Net Turnover	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A - Agriculture, forestry and fishing	0.79	0.93	0.83	0.86	0.97	1.08	1.02	1.28	1.04	0.99	0.84	0.71
B - Mining and quarrying	0.38	0.45	0.31	0.28	0.33	0.36	0.44	0.90	1.23	1.05	1.04	0.92
C - Manufacturing	0.10	0.11	0.11	0.09	0.10	0.09	0.09	0.10	0.11	0.11	0.11	0.11
D - Electricity, gas, steam and air conditioning supply	0.10	0.16	0.21	0.14	0.14	0.12	0.13	0.15	0.23	0.16	0.25	0.23
E - Water supply; sewerage; waste managment and remediation activities	0.39	0.49	0.48	0.39	0.39	0.36	0.34	0.34	0.33	0.29	0.24	0.21
F - Construction	0.44	0.46	0.48	0.42	0.41	0.39	0.35	0.33	0.31	0.26	0.22	0.20
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	0.08	0.09	0.08	0.08	0.08	0.07	0.07	0.06	0.06	0.05	0.05	0.05
H - Transporting and storage	1.01	1.07	1.06	0.93	0.87	0.79	0.73	0.66	0.58	0.53	0.46	0.40
I - Accommodation and food service activities	0.09	0.09	0.10	0.08	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.04
J - Information and communication	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.02	0.02	0.02	0.02	0.02
K - Financial and insurance activities												
L - Real estate activities	0.11	0.11	0.12	0.09	0.08	0.07	0.07	0.07	0.06	0.06	0.05	0.05
M-Education	0.16	0.17	0.16	0.15	0.14	0.13	0.12	0.11	0.10	0.09	0.08	0.07
N-Health and social work	0.22	0.25	0.27	0.24	0.24	0.23	0.20	0.20	0.18	0.17	0.16	0.15
O-Other community, social and personal service activities												
P-Private household with employed persons												
Q-Extra -territorial organziations and bodies												
tot-Total	0.21	0.23	0.23	0.20	0.20	0.19	0.18	0.18	0.17	0.15	0.14	0.13

Table 12: The percentage of net turnover that a sector pays as carbon tax to the Swedish government over the period from 2008 to 2019. Green cells indicate that a sector paid relatively few of its net turnover to the carbon tax.

Emissions per net turnover

Emissions (tonnes) per Net Turnover (million eur)	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
A - Agriculture, forestry and fishing	167	180	162	153	164	167	155	154	146	137	120	115
B - Mining and quarrying	229	265	201	189	208	230	253	283	291	243	225	207
C - Manufacturing	101	96	108	91	90	89	86	89	87	81	74	71
D - Electricity, gas, steam and air conditioning supply	332	360	402	328	300	294	273	271	288	275	249	197
E - Water supply; sewerage; waste managment and remediation activities	66	79	71	62	64	63	59	57	57	51	44	41
F - Construction	44	44	44	41	38	37	34	32	29	24	22	22
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	9	8	8	8	7	7	6	6	6	5	5	5
H - Transporting and storage	284	292	264	208	193	207	217	238	241	200	179	166
I - Accommodation and food service activities	9	9	9	8	7	7	6	6	5	5	5	4
J - Information and communication	5	5	4	4	4	3	3	2	2	2	2	2
K - Financial and insurance activities												
L - Real estate activities	11	11	12	9	8	7	7	6	6	5	5	5
M-Education	16	16	15	15	13	12	11	10	9	8	8	7
N-Health and social work	23	24	25	24	22	23	20	19	17	16	16	16
O-Other community, social and personal service activities												
P-Private household with employed persons												
Q-Extra -territorial organziations and bodies												
tot-Total	73	71	75	63	60	59	56	55	53	48	44	41

Table 13: The amount of emissions (in tonnes) per net turnover (millions of Euro's) per sector over the period from 2008 to 2019. Green cells indicate that a sector has relatively few emissions per net turnover.

A.5 Carbon tax & EU ETS

Freely allocated allowances

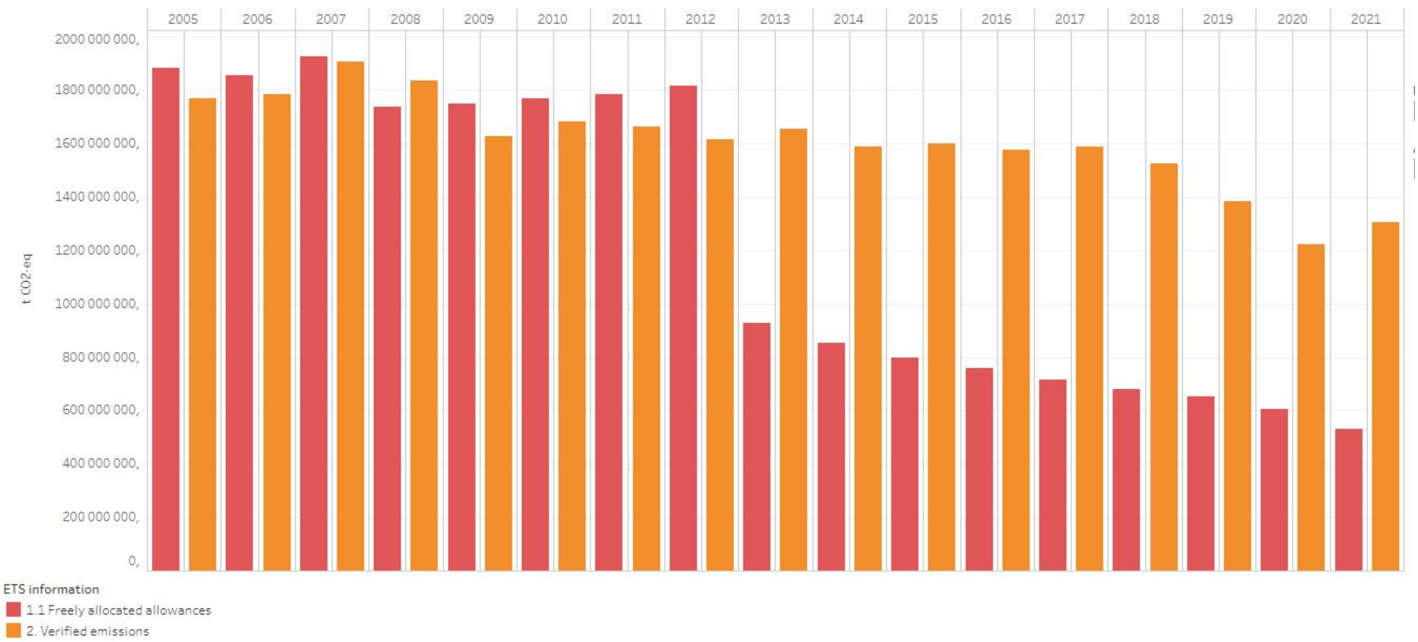


Figure 10: Freely handed out allowances compared to verified emissions of the EU ETS. The figure covers the full sample period (2005-2021). The data is obtained from the European Environment Agency, part of the European Union.

<table>
<tr><th colspan="6">Carbon tax rates (SEK/kg)</th></tr>
<tr><th>Year</th><th>Standard rate</th><th>Manufacturing rate</th><th>General exemptions</th><th>Cement, glass lime</th><th>Firms in EU ETS</th></tr>
<tr><td>1990</td><td>No tax</td><td>No tax</td><td>No tax</td><td>No tax</td><td rowspan="15">Before EU ETS</td></tr>
<tr><td>1991</td><td>0.25</td><td>0.25</td><td>Manufacturing rates if CO_2 + Energy tax<= 1.7% of sale, untaxed further emissions</td><td>Manufacturing rates if CO_2 + Energy tax<= 1.7% of sale, untaxed further emissions</td></tr>
<tr><td>1992</td><td>0.25</td><td>0.25</td><td>Manufacturing rates if CO_2 + Energy tax<= 1.2% of sale, untaxed further emissions</td><td>Manufacturing rates if CO_2 + Energy tax<= 1.2% of sale, untaxed further emissions</td></tr>
<tr><td>1993</td><td>0.32</td><td>0.08</td><td rowspan="4">Manufacturing rate</td><td rowspan="4">Industry rate up to 1.2 % of sales, untaxed further emissions ("1.2% rule")</td></tr>
<tr><td>1994</td><td>0.32</td><td>0.08</td></tr>
<tr><td>1995</td><td>0.34</td><td>0.09</td></tr>
<tr><td>1996</td><td>0.37</td><td>0.09</td></tr>
<tr><td>1997</td><td>0.37</td><td>0.19</td><td rowspan="14">Manufacturing tax rate up to 0.8% of sales, exceeding emissions: 25 % of general manufacturing CO_2 tax rate ("0.8 % rule")</td><td rowspan="8">0.8% rule is applied first, emissions exceeding 1.2 % of sales are untaxed</td></tr>
<tr><td>1998</td><td>0.37</td><td>0.19</td></tr>
<tr><td>1999</td><td>0.37</td><td>0.19</td></tr>
<tr><td>2000</td><td>0.37</td><td>0.19</td></tr>
<tr><td>2001</td><td>0.53</td><td>0.19</td></tr>
<tr><td>2002</td><td>0.63</td><td>0.19</td></tr>
<tr><td>2003</td><td>0.76</td><td>0.19</td></tr>
<tr><td>2004</td><td>0.91</td><td>0.19</td></tr>
<tr><td>2005</td><td>0.91</td><td>0.19</td><td rowspan="13">Special exemption removed</td><td rowspan="3">Manufacturing rate + exemptions where applicable</td></tr>
<tr><td>2006</td><td>0.92</td><td>0.19</td></tr>
<tr><td>2007</td><td>0.93</td><td>0.20</td></tr>
<tr><td>2008</td><td>1.01</td><td>0.21</td><td rowspan="3">EU ETS+15% of standard rate for plants under EU ETS</td></tr>
<tr><td>2009</td><td>1.05</td><td>0.22</td></tr>
<tr><td>2010</td><td>1.05</td><td>0.22</td></tr>
<tr><td>2011</td><td>1.05</td><td>0.315</td><td rowspan="4">Manufacturing rate up to 1.2%: Exceeding: 24% of manufacturing rate</td><td rowspan="7">No CO_2 tax for installations covered by EU ETS</td></tr>
<tr><td>2012</td><td>1.05</td><td>0.32</td></tr>
<tr><td>2013</td><td>1.05</td><td>0.32</td></tr>
<tr><td>2014</td><td>1.05</td><td>0.32</td></tr>
<tr><td>2015</td><td>1.05</td><td>0.63</td><td rowspan="3">Special exemption removed</td></tr>
<tr><td>2016</td><td>1.12</td><td>0.90</td></tr>
<tr><td>2017</td><td>1.13</td><td>0.90</td></tr>
</table>

Figure 11: The evolution of the Swedish Carbon tax in detail up to 2017. Tax rates are denoted in SEK/kg, such that it converts to SEK per tonne by multiplying the rate by 1000. The figure is obtained from Martinsson et al. (2022).