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FEP FACULDADE DE ECONOMIA
UNIVERSIDADE DO PORTO

Informational Efficiency of Carbon Emission Trading Schemes – Adjusted Market Inefficiency Magnitude applied to China and European Markets

David Ferreira Brandão

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Júlio Fernando Seara Sequeira da Mota Lobão Ph.D.

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Resumo

O conceito de eficiência informacional nos mercados financeiros, com base na Hipótese dos Mercados Eficientes, proposta por Fama (1970), estabelece que os preços dos ativos reflete toda a informação disponível no mercado. Esta é uma característica desejável dos mercados financeiros uma vez que promove uma melhor alocação de recursos entre os agentes do mercado, contribuindo assim para o bem-estar social e económico. Neste estudo, analisámos a eficiência informacional dos mercados de emissões de carbono, com foco no Sistema Nacional de Comércio de Emissões da China, assim como nos mercados piloto de comércio de emissões desta e no Sistema de Comércio de Emissão da UE. Para avaliar a eficiência informacional destes mercados e a sua evolução ao longo do tempo, utilizámos a Magnitude Ajustada de Ineficiência de Mercado. Este indicador, elaborada por Vu Le Tran et al. (2019), é caracterizada por baixo encargo computacional e fácil interpretação dos resultados.

O período de análise do Sistema de Comércio de Emissões da UE diz respeito ao periodo desde a criação do mercado até ao dia 10 de outubro de 2023, enquanto que tanto para os mercados piloto como para o mercado nacional de emissões Chinês o período refere-se desde a criação dos mercados até ao dia 29 de Setembro de 2023. Os resultados indicam que o Sistema de Comércio de Licenças de Emissão da UE é atualmente um mercado eficiente, uma vez que os resultados obtidos para o indicador computado não mostram violações da hipótese do mercado eficiente estabelecido por Fama (1970). Para os restantes mercados, descobrimos que apenas os mercados de Pequim e Tianjin são atualmente informacionalmente eficientes. Estes dois mercados são seguidos por Shenzhen, Guangdong, o Sistema Nacional de Comércio de Licenças de Emissões da China, Fujian, Chongqing, Xangai e Hubei, por ordem decrescente de eficiência. Estes resultados têm implicações na formulação de políticas e benefícios sociais. Aumentar a eficiência do mercado pode levar a uma melhor alocação de recursos, o que, portanto pode resultar em reduções de emissões mais eficazes. Os reguladores podem usar estas implicações de forma a melhorar a estrutura e a implementação dos esquemas de comércio de emissões, a fim de alcançar uma maior eficiência no futuro.

Palavras-chave: Magnitude Ajustada de Ineficiência de Mercado; Sistemas de comércio de licenças de emissão; Eficiência Informacional; Teoria da aleatoriedade dos retornos

Abstract

The concept of informational efficiency in financial markets, based on the Efficient Market Hypothesis (EMH) proposed by Fama (1970), posits that asset prices fully reflect all available information. This is a desirable characteristic of financial markets, as it promotes a better allocation of resources among market participants, thereby improving social and economic welfare. In this study, we analysed the informational efficiency of carbon emission trading schemes, focusing on China's National Emission Trading Scheme (ETS), China's pilot emission trading scheme markets, and the European Union Emission Trading Scheme (EU ETS). Informational efficiency, as first established by Fama (1970), refers to how well market prices reflect all available information. To assess the informational efficiency of these markets and how it evolves over time, we utilized the Adjusted Market Inefficiency Magnitude (AMIM). This measure, elaborated by Vu Le Tran et al. (2019) is advantageous due to its low computational burden and straightforward interpretation of results.

The data set used for the EU ETS covers the period from the market inception until 10th of October 2023 while for the China National ETS and China pilot markets it covers the period from inception until the 29th of September 2023. Our empirical results indicate that the EU ETS is currently an informationally efficient market, as the AMIM results show no violations of the efficient market hypothesis. For China's emission trading schemes, we found that only the markets in Beijing and Tianjin are currently informationally efficient. They are followed by Shenzhen, Guangdong, the National Emission Trading Scheme, Fujian, Chongqing, Shanghai, and Hubei, in descending order of informational efficiency. These findings have significant implications for policymaking and social benefit. Enhancing market efficiency can lead to better resource allocation, which in turn can result in more effective emission reductions. Policymakers can use these insights to improve the design and implementation of emission trading schemes to achieve greater efficiency in the future.

Keywords: Adjusted Market Inefficiency Magnitude (AMIM); Emission Trading Scheme (ETS); Informational efficiency; Random Walk

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1. Introduction

The increasing recognition of climate change as a critical global issue has led to the development and implementation of various mechanisms aimed at reducing greenhouse gas emissions. Among these, carbon emission trading schemes (ETS) have emerged as a key policy tool in the fight against climate change. The fundamental premise of an ETS is to create a market for carbon emissions by setting a cap on the total amount of greenhouse gases that can be emitted by covered entities. Companies receive or buy emission allowances that they can trade with one another as needed. This market-based approach incentivizes companies to reduce their emissions, as they can sell excess allowances if they emit less than their allocated share or purchase additional allowances if they exceed it.

The European Union Emission Trading Scheme (EU ETS), launched in 2005, is one of the most established and widely studied carbon markets in the world. It has served as a model for other regions and countries, including China, which has recently implemented its own national ETS after several years of regional pilot programs. The effectiveness of these schemes in reducing emissions, however, depends heavily on their design, implementation, and the informational efficiency of the markets they create.

Informational efficiency in the context of financial markets such as ETSs refers to the degree to which prices reflect all available information, including regulations, technological advancements, and market conditions as defined by Fama (1970). An efficient market ensures that prices provide accurate signals for investment avoiding noise trading and their costs as explored in Shleifer et al. (1990), leading to a better resource allocation process.

The motivation for this dissertation comes from the growing relevance of carbon markets in achieving environmental objectives, and therefore the understanding of these markets efficiency in achieving it. Despite the importance of this topic, there is a lack of studies that use recent data and employ a structured methodological approach to analyse market efficiency in ETSs. This study fills this gap by using the Bai et al. (1998) method to dynamically determine the windows of analysis, rather than relying on fixed windows as in previous works. The dataset covers the EU ETS from its inception until October 10, 2023, and the China National ETS and pilot markets from their inception until September 29, 2023. The dissertation applies the Adjusted Market Inefficiency Magnitude (AMIM) metric, developed by Vu Le Tran et al. (2019), to assess and compare the efficiency of both the EU ETS and China's emerging ETS, a method which measures the efficiency of the market based

on a standardized value which consider the magnitude of the coefficients obtained from an autoregressive model applied on the different windows of estimation.

The results revealed significant variability in the informational efficiency of the ETS across different markets and periods. While the EU ETS initially displayed moderate inefficiency, it generally progressed towards greater efficiency, although with some fluctuations. Conversely, the Chinese National ETS began with a relatively efficient state but declined as it matured, due to factors such as low liquidity and market immaturity. Among the Chinese pilot markets, Beijing and Tianjin have shown improvements, whereas markets like Chongqing and Guangdong demonstrated persistent inefficiencies.

This dissertation makes several significant contributions to the existing literature on carbon emission trading schemes (ETS) and market efficiency. One of the primary contributions is the application of the Adjusted Market Inefficiency Magnitude (AMIM) metric, a relatively easy to interpret tool in the field. By employing the AMIM, this dissertation offers a practical and innovative approach to evaluate market efficiency, providing insights that are both robust and easily interpretable.

Additionally, the dissertation conducts a comparative analysis of the European Union Emission Trading Scheme (EU ETS) and various Chinese ETS markets, including the recently established national scheme. This comparison between a mature, well-established market and emerging markets provides valuable insights into the factors that influence market efficiency across different regulatory and economic contexts. The findings from this analysis are crucial for identifying best practices and potential challenges in the design and implementation of carbon trading systems in diverse regions.

Moreover, the dissertation offers important policy implications for market design. The insights derived from this study have direct relevance for policymakers involved in the development and operation of carbon markets. By highlighting the strengths and weaknesses of current systems, particularly concerning their informational efficiency, the dissertation provides recommendations for enhancing market structures to better achieve objectives. This includes suggestions for improving transparency, regulatory oversight, and market liquidity to ensure that carbon prices accurately reflect underlying information.

Finally, the dissertation contributes to the academic literature on carbon markets and market efficiency by providing empirical evidence from two of the world's most significant carbon markets. The findings and methodologies presented in this work enrich the ongoing

discourse on optimizing these markets to drive effective climate action and can serve as a valuable reference for future research in the field.

The structure of the rest of the dissertation is organized as follows. The second chapter provides a comprehensive literature review, examining the origins of the emission trading schemes, their environmental, social and economic impact and finally studies on their informational efficiency. This review aims to establish the current state of knowledge in the field. The third chapter delves into the methodology employed in this work which closely tracks the methodology employed in Vu Le Tran et al. (2019), it also presents the data set used in this dissertation as well as its analyses. The fourth chapter presents the results achieved with the data set and the methodology employed. In the fifth chapter, the results are discussed and compared with findings from other studies. The sixth chapter encompasses our robust tests and their comparison with the results discussed in the fifth chapter. Finally, the seventh chapter concludes the dissertation with a summary of the findings and their implications.

2. Literature Review

2.1. Climate change and the appearance of emission trading schemes

Climate change is a major challenge of the 21st century, with the world's leading economies still heavily reliant on fossil fuels, driving significant environmental changes. Numerous studies highlight the impact of human activities on global temperature rise.

Schnur et al. (2005) used a Bayesian approach to detect climate change, finding strong evidence that human activities, particularly greenhouse gas emissions, are key drivers of observed temperature increases. Hansen et al. (2007) stressed the need for urgent action, suggesting that limiting global warming to below 1ºC could prevent catastrophic consequences. Their study called for reducing CO2 emissions, cutting non-CO2 forcings, and minimizing aerosol warming effects.

The IPCC's "Climate Change 2021: The Physical Science Basis," part of its Sixth Assessment Report (AR6), attributes the current climate crisis largely to human activities and extreme emissions.

Emissions trading, or 'cap and trade,' is a cost-effective method to reduce greenhouse gas emissions. The government sets a cap on allowable emissions and issues permits, which firms can trade. This market-based approach encourages companies to innovate and reduce emissions, leading to a single permit price that fluctuates with economic conditions. Research shows that emissions trading systems have driven innovation in low-carbon technologies, such as renewable energy and energy efficiency, helping to reduce greenhouse gas emissions.

2.2. Emission Trading Schemes Origins

For a historical overview of emissions markets, we can begin with Coase (1958), who introduced the concept of property rights linked to emissions. Coase suggested that allowing market transactions of these rights would naturally lead to equilibrium and optimal utilization. Pigou (1960) proposed a tax on polluters for each unit of emissions, but he acknowledged the difficulty of implementing such a tax due to the continuous nature of emissions in the market. Dales (1968) also explored this issue, while Crocker (1966) highlighted the importance of these markets in providing price signals. These signals, according to Crocker, would give regulators critical data for shaping policy. This already aligns with the purpose of our study, which focuses on understanding the mechanisms and behaviour of carbon markets.

As awareness of the environmental impact of fossil fuel-based economies grew, emissions trading schemes were developed. A significant step in this direction was the adoption of the Kyoto Protocol on December 11, 1997, in Kyoto, Japan, during the third Conference of the Parties (COP 3) to the United Nations Framework Convention on Climate Change (UNFCCC). This marked the first major international effort to address emissions and climate change through a market-based mechanism.

The UK's launch of its Emissions Trading Scheme in 2002 significantly influenced Europe's perception of carbon markets, especially after the US withdrew from the Kyoto Protocol in 2001. Following Germany's support in December 2002, the EU adopted the directive to create the EU Emissions Trading Scheme (EU ETS) in July 2003, officially launching it in January 2005.

Globally, the Chicago Climate Exchange (CCX) operated from 2003 to 2010 as a voluntary carbon trading platform. California's Cap-and-Trade Program, established in 2006, began in 2012 to reduce greenhouse gas emissions in the industrial and energy sectors. The Regional Greenhouse Gas Initiative (RGGI), launched in 2009, involves ten Northeastern US states, focusing on capping emissions from the electricity sector.

Other regions and countries have also developed carbon markets. Australia planned to link its carbon market with the EU ETS in 2015, while New Zealand's Emission Trading Scheme (NZ ETS) began in 2008 and expanded in 2010. Additionally, Japan, South Korea, Brazil, and Mexico have laid the legislative groundwork for future carbon markets.

China initiated a series of regional carbon markets in several provinces and cities, including Beijing, Shanghai, Shenzhen, and Guangdong, which started around 2013. These programs were designed to test emissions trading mechanisms and gather experience before creating a national program. The national program which is called National Emissions Trading Scheme (ETS) was officially launched in February 2021 with a focus on the power generation sector which due to the population size is one of the most significant in the country, the plan is expected to reach other sectors over time. The Emission trading scheme imposes emission caps on more than 2,000 companies and allows for emissions trading within specified limits. Companies exceeding their emission limits were required to purchase additional allowances or reduce emissions.

According to Calel (2013), the global carbon market had quickly grown into a $175 billion per year industry, marking a significant success in climate policy, but it remained poorly

understood and under-scrutinized by economic agents. By 2023, the market value reached a record $949 billion, with the European Union's Emissions Trading System (EU ETS) representing 87% of the global market, and the UK ETS, launched in 2021, accounting for 4% (Tiseo, 2024).

This rapid growth highlights the importance of studying market efficiency. A limited understanding of the carbon market's characteristics and mechanisms can lead to suboptimal policy decisions, hindering the market's potential. If the market does not follow the Efficient Market Hypothesis (Fama, 1970), informed agents might exploit its behavior, disrupting the ideal resource allocation proposed by Coase (1958). Despite future regulatory changes, the carbon market remains a key pillar of global climate policy.

2.3. Impacts of Emission Trading

Now that we've introduced emissions trading schemes (ETS), we should assess whether they have significantly contributed to emission reductions. Villoria-Saez et al. (2016) found that carbon emissions decreased by an average of 1.58% annually in regions with ETSs, including the EU, Australia, New Zealand, Japan, the US, and Canada. Over 10 years, these regions achieved a 23.43% reduction in CO2 emissions compared to trends without ETSs. The study also proposed country-specific equations to determine necessary emission reductions through appropriate penalty levels. This evidence suggests that ETSs have had a measurable and positive impact on reducing carbon emissions, proving effective as an environmental policy tool.

Now shifting to China's pilot emissions trading schemes (ETS), which are a key focus of this work, Wu et al. (2023) provide evidence of their effectiveness in the iron and steel industry. The study uses a data envelopment approach to construct CO2 emission efficiency and applies the synthetic control method to assess the ETS's impact.

The results show that the ETS significantly improved CO2 emission efficiency in pilot provinces, with a 5% significance level compared to a counterfactual scenario. The study employed a method similar to using a dummy variable to check the additive effect on emission levels. This improvement highlights the ETS's role in enhancing industrial CO2 efficiency, with effectiveness varying across provinces due to differing regional policies. The positive impact grows over time, indicating cumulative benefits as the market matures.

These findings emphasize the ETS's importance in China's carbon reduction efforts, particularly in improving emission efficiency in a key industrial sector. As the ETS matures, its impact on emission reductions becomes increasingly significant, supporting broader adoption and enhancement of carbon trading mechanisms.

Still focusing on China's pilot markets, the study of Du et al. (2022), examined whether these schemes effectively reduce pollution and improve energy efficiency. The results showed that the ETSs effectively reduced pollutant emissions from enterprises, bringing significant environmental benefits. This reduction was achieved despite potential increases in production scale. The policy encourages enterprises to adopt cleaner production practices, leading to a significant reduction in pollutant generation. By focusing on source control and cleaner production, the ETSs help enterprises achieve a win-win situation, improving both environmental outcomes and economic efficiency in the long term.

Although not the primary focus of the paper, the authors also addressed energy efficiency. Their results suggest that the shift to cleaner production driven by the ETSs may also improve energy efficiency. They found that ETSs significantly improved fossil energy efficiency by approximately 7.5%. These results are consistent and robust across various tests, including instrumental variable methods and DDD estimations, which ruled out other policy interferences. The improvement in fossil energy efficiency is mainly achieved through a decrease in coal consumption and an improvement in the quality of intermediate inputs, rather than through technological innovation.

Many other studies examine China's case. For example, Huang et al. (2022) found that the average carbon emissions intensity decline rate for ETS pilots was 7.3% from 2013 to 2018 and for non-pilot regions, the average decline rate was 4.92% during the same period. This demonstrates that ETS has a significantly positive impact on emission reduction in pilot regions.

Zhang et al. (2020), using panel data from 2004 to 2015, found that ETS pilots reduced emissions by about 16.2%. Hu et al. (2020), using the DID model on provincial industrial data from 2005 to 2015, concluded that ETS pilots had lower energy consumption and CO2 emissions compared to non-pilot areas. Hu et al. (2020), using a DID model on data from 2007 to 2016, discovered that regions with higher development levels had less emission reduction impact, with the western region showing the most substantial reductions. Qi et al.

(2021), using provincial data from 2008 to 2016, found significant reductions in carbon emissions, emissions intensity, and fossil energy consumption in ETS pilot regions.

These studies collectively demonstrate that China's ETS has effectively reduced emissions and improved energy efficiency, though the impact varies across regions and development levels.

2.4. Efficiency studies on Emission Trading Schemes

Many other works have already conducted informational efficiency measurement on emission trading schemes, most works have focused their analysis on the European Union Emission Trading Scheme and on the Chinese Pilot Markets.

Many methodologies have been used. In this literature comprehensive review, we analyzed and summed up some of the results reached using different methodologies to the one applied by us, which is the Adjusted Market Inefficiency Magnitude introduced by Vu Le Tran et al. (2019).

Montagnoli et al. (2010) examined the informational efficiency of the EU ETS during Phase I, from June 27, 2005, to December 28, 2007, and Phase II, from February 26, 2008, to December 30, 2009, using a unit root test (Variance Ratio). This test checks if the variance of returns follows a random walk, indicating market efficiency. The study found that Phase I did not meet the Efficient Market Hypothesis (EMH) for any holding period, while Phase II met the EMH for only two of four holding periods.

Since the VR test has limitations, such as size distortions due to sequential trading and the assumption that test statistics at different time intervals or holding periods are uncorrelated, the authors also conducted a non-parametric VR test. This test confirmed the inefficiency of Phase I but was unable to reject the EMH for Phase II. Additionally, the automatic VR test, as proposed by Choi (1999) and Kim (2009), contradicted earlier findings, indicating no violation of the EMH. Overall, the study indicates that the EU ETS demonstrated improved efficiency from Phase I to Phase II. Although the sample is limited and only covered the first four years of the EU ETS's life, one can already see that the market shows changes in efficiency since the results in Phase II of the scheme are not as clear as those in Phase I.

With a similar approach Goers (2013) used unit root tests, variance ratios, and autocorrelation analysis to examine the EU ETS across two periods: Phase I (August 2005 to December 2007) and Phase II (January 2009 to June 2012). In Phase I, significant

autocorrelation and variance ratio results indicated that the market did not follow a random walk, suggesting a lack of informational efficiency. However, in Phase II, autocorrelation was not significant, and variance ratios supported the random walk hypothesis, implying improved market efficiency. Unit root tests also showed that prices in Phase I were non-stationary, indicating potential randomness, while Phase II results were more ambiguous but suggested price stationarity. Overall, by applying unit root, autocorrelation, and variance ratio tests, evidence is derived that the results for the first trading period of the EU ETS suggest the absence of informational efficiency, whereas in the second trading period, the market shows signs of evolution.

Now shifting to a different methodology to analyse the informational efficiency of the EU ETS, Daskalakis (2013) used technical analysis rules to measure this efficiency. The methodology compares the profitability of technical rules to benchmark strategies; higher profitability than the benchmarks suggest a less efficient market with predictable patterns and therefore there a low level of complexity and of informational efficiency. The analysis covered three technical rules—variable length moving average (VMA), trading range break-out (TRB), and random walk (RW)—against buy-and-hold (BH) and sell-and-hold (SH) strategies, using data from futures contracts issued between January 2008 and December 2011, covering Phase II of the EU ETS. To evaluate the performance of the strategies against the benchmarks, the author selected metrics such as the profitability index, average daily return, cumulative return, standard deviation, coefficient of variation, and Sharpe ratio. The author acknowledges that since this period was extremely bearish for the carbon allowances, the buy-and-hold strategy would not be the best benchmark against the trading rules selected. In fact, that benchmark is beaten in every case. However, even when comparing the sell-and-hold strategy, the RW and VMA outperformed the SH. For all carbon futures (which were divided by the year of issuance), the profit factor of the RW, VMA, and TRB was higher than the profit factor of the SH. In terms of strategy volatility, the author found that the standard deviation results suggest that the TRB returns exhibit the lowest variability, followed by the RW, the VMA, and the SH. However, from 2010 onwards, the EU ETS shows signs of market efficiency and maturity since the strategies started to become relatively less profitable when analysing their performance against the benchmarks.

Another methodology was employed by Charles et al. (2013) used the cost-of-carry model to assess EU ETS market efficiency during Phase II (March 13, 2009, to January 17, 2012)

across BlueNext, EEX, and ECX markets. They found that the cost-of-carry hypothesis was often rejected, indicating inefficiency, as futures and spot prices diverged, creating arbitrage opportunities despite strong long-run correlations suggesting a lack of market efficiency. Still within the cost-of-carry model approach, Joyeux et al. (2010) applied the cost-of-carry model to Phase I data from December 2006 to December 2007, finding that the model did not hold for futures expiring in 2006 but did for those expiring in 2007.

Now focusing on the efficiency of China's carbon markets, the paper written by Chen et al. (2022) uses the Hubei pilot market as a benchmark to study the informational efficiency of these emission trading schemes in China. To check if the Hubei Carbon Pilot Market is characterized by market efficiency and therefore follows a random walk, the authors used a test called VR (Variance Ratio) and its wild bootstrapping. The null hypothesis of this test suggests that the market is efficient and should be accepted if there is no statistical significance associated with the VR ratio. The VR test mainly consists of testing EMH against stationary alternatives, by exploiting the fact that the variance of random walk increments is linear. The data used in this wor ranges from April 2nd, 2014, to August 31st, 2020. When applying the wild bootstrapped VR to the data, the market was found to be not efficient, suggesting that the market is in a weak form of efficiency. The authors also checked the evolution of the efficiency of the market by creating subsamples and computing the VR for those samples. It was found that the market efficiency has been generally in a state of continuous improvement, but still in a weak form of efficiency.

To explain why the markets are at this state, they defined three drivers of inefficiency: non-active trading, deficiency of legal basis, and low degree of marketization. To improve market efficiency, the authors suggest three measures. Firstly, the inception of a mechanism of market stability reserve, which will ease the volatility of the carbon price by providing more liquidity when the demand for allowance exceeds the supply and decreasing it when the supply exceeds the demand. Secondly, diversification of the financial products available on the schemes so that participants can meet their risk management needs. Finally, the transfer of the allowance allocation mode from the free distribution to auctioning would shift the allocation process from one that can be biased by the commanded corporate available information by the government and the fairness of the process to a more efficiency-driven process of allocation.

With a similar approach in some points, Zhao et al. (2017) developed a more complete work where they tested the informational efficiency of more China's pilot markets. The methodology used was unit root and run test. The data used is based on the period from June 18, 2013, to September 23, 2015. Using the Augmented-Dickey Fuller test, the authors reached the conclusion that the markets of Beijing, Shanghai, Shenzhen, and Tianjin have achieved the weak form of efficiency, which means that market investors cannot predict the price according to historical information. The run test results indicate a transition within the carbon trading market, moving from an inefficient state towards weak efficiency as the market has grown in scale, experienced higher trading volumes, seen improvements in market liquidity, and witnessed ongoing enhancements in its underlying mechanisms.

Another type of methodology used to check the EMH is called entropy, more precisely different types of information entropy which is basically a concept that checks the amount of randomness in a series, the higher the entropy the higher the randomness and therefore the most likely the series follows a random walk and therefore respects the efficient market hypothesis.

Liu et al. (2021) used fuzzy entropy to assess the information efficiency of China's carbon markets, employing an efficiency index developed by Alvarez et al. (2012). This index compares fuzzy entropy to Gauss white noise entropy, with a higher ratio indicating greater information efficiency. Data from June 23, 2014, to June 27, 2019, showed that Hubei was the most information-efficient of China's pilot markets, followed by Guangdong, Beijing, Shanghai, Shenzhen, Chongqing, and Tianjin. The EU market was the most efficient overall. Increased trading activity in the EU, Hubei, and Guangdong led to higher information efficiency, while lower trading activity resulted in less efficiency. The study also examined time-varying efficiency using a sliding window approach, revealing that Hubei and Guangdong maintained relatively high efficiency, Beijing and Shanghai were around 50%, and Shenzhen, Chongqing, and Tianjin fell below 10% at times.

The authors attribute variations in information efficiency to several factors. Firstly, the allowance allocation mechanisms play a role. For instance, in Chongqing and Guangdong, efficiency was below 10% before June 2017 due to the self-declared allowance mode, which led to excessive allowances and insufficient trading intention. Secondly, transaction rules impact efficiency; widening the range for falling price limits increases efficiency, as more

control over price limits enhances predictability. Finally, the penalty system affects efficiency—lower penalties reduce trading activity, thus decreasing efficiency.

The study also highlights the entropic correlation between markets, showing that despite operating independently, China's pilot markets are interlinked due to regional economic connections and shared trading sentiment. To improve market efficiency, the authors recommend focusing on auction mechanisms for carbon allocation, adjusting price limits, establishing effective penalty systems to incentivize trading, and promoting innovation in carbon financial derivatives.

Yin et al. (2018) analysed the complexity and maturity of China's carbon markets using the Modified Multi-Scale Entropy (MMSE) method. The process involves two steps: first, scaling the data using moving averages to eliminate unidentified entropy, and second, measuring entropy with the scaled data. Their analysis, based on data from each pilot market up to the end of 2017, revealed that entropy levels were consistently lower than white noise, indicating low complexity and efficiency.

The study found that complexity decreased with longer time scales, suggesting distinct factors affecting market efficiency on shorter scales (less than one month), while longer time scales (over one month) were influenced by more regular trends. This implies that short-term fluctuations are driven by irregular factors, while long-term trends are smoother and more predictable.

Another paper that used entropy-based analysis was the one conducted by Liu et al. (2019), who used a time-varying Hurst index and an entropy-based TOPSIS model to assess the maturity of China's carbon markets. Their evaluation system includes internal factors (market size, operation efficiency, and quality), external factors (macro-environment, government policies, allowance allocation, and system design), and interface factors (supervision, monitoring, reporting, and verification). By analysing 32 indicators from 2013 to 2017, the study found that China's pilot carbon markets generally have low maturity, with notable variations among them. The Hubei market was the most mature, followed by Guangdong, Shenzhen, Beijing, Shanghai, Tianjin, and Chongqing, which was the least mature.

To conclude, Fan et al. (2018) conducted a different approach called Multifractal Detrended Fluctuation Analysis on seven China's pilot carbon markets to evaluate their informational efficiency. To check the randomness of the series, the authors used the Hurst exponent. When this indicator is less than 0.5, it suggests mono-fractal series, which means that the

series is not characterized by patterns and correlations that repeat over time. This is evidence of randomness associated with market efficiency. When it is higher than 0.5, we have multi-fractality, which suggests higher levels of correlation and trends at different scales, indicating a lack of market efficiency.

The study used daily carbon trading prices from the start of the Chongqing pilot market to February 9, 2018. The authors identified asymmetric price distributions and a general Hurst exponent in the time series, indicating inefficiency. They measured efficiency using the Hurst exponent spectrum, where a value of 0 represents efficiency and higher values denote greater inefficiency. Results for all seven markets were above one, suggesting inefficiency, except for Tianjin. The time-varying analysis showed that short-term efficiency varied across markets and over time.

Now that we have covered the results and conclusions of all these works, the next section of the work will focus on the methodology employed in our dissertation so that one can understand what will be done to analyse the informational efficiency of the markets we choose to analyse.

3. Methods and Data

3.1. Methods

To study the informational efficiency of China's Carbon Pilot Markets, China's National Emission Trading Schema, and finally the European Union Emission Trading Scheme, the methodology employed in this study is the one introduced by Vu le Tran et al. (2019). This measure of market efficiency allows for both efficiency measure and the evolution of this efficiency.

This measure of efficiency is called Adjusted Market Inefficiency Magnitude (AMIM), and there are five steps that should be taken to construct it. The steps are as follows: (1) model estimation; (2) normalization of autocorrelation coefficients; (3) computation of the Market Inefficiency Magnitude (MIM); (4) construction of confidence intervals; (5) computation of the of the Adjusted Market Inefficiency Magnitude (AMIM) In this section of the dissertation, we will go through each one of those steps.

(1) Model Estimation

According to Fama (1970), an efficient market is one where securities prices reflect all available information, therefore it should not be possible to predict stock prices. According to this theory the efficiency of a market can takes three different forms, weak form, semi-strong form, and strong form. On the strong form of efficiency, it is stated that all information (historical, publicly available and inside information) is reflected on the pricing process of a security. This phenomena is associated with the random walk theory, if no one can get excess return then the prices follow a random walk which means that no agent can predict them, this does not mean that agents will not achieve returns, in fact the random walk theory states that the distribution of returns will follow a normal distribution meaning that half of the market will achieve positive returns not based on their ability to predict returns but by luck.

Based on this theory the model estimated for each time series in our data was an autoregressive model of returns. This autoregressive model will therefore have as dependent variable the return on day t and as explanatory variables the lag value of that t day return, which will be the previous trading days' returns.

$$r_t = \propto + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \cdots + \beta_q r_{t-q} + \varepsilon_t \quad (1)$$

According to the EMH since prices already reflect all available information, returns cannot be predicted by past information (past returns) therefore on equation (1) if we are analysing an efficient market the coefficients are expected to be near zero and statistical insignificant. On the contrary case, if there are statistically significant coefficients, with high marginal effects and in the case of even more than one of coefficients with those characteristics that will be evidence against the EMH. Since markets go through different structural periods that cannot be compared straightway, we defined windows of estimation for this regression for each one of the markets, this was achieved by establishing structural break points which were computed by conducting the Bai-Perron test for structural breaks, as detailed by Bai et al. (1998). The optimal number of lags in each one of these regressions/windows was computed using the Akaike Information Criteria as defined by Akaike (1974), this is a methodology that measures the information loss in the model and defines the optimal number of lags based on trade-off between the simplicity of the model and the goodness of the fit on the model.

(2) Normalization of autocorrelation coefficients

After estimating the autoregression model on the step above one will get a set of coefficients. Those coefficients will have different standard errors and therefore can be correlated, due to this there is a violation of one of the classical hypotheses and therefore estimates and inferences can be compromised. To solve this under this methodology the approach will be the following, first one needs to extract the estimated coefficients ($\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_q$) obtained on the regression (1) and store them on a vector denominated by $\hat{\beta}$. This vector will follow an asymptotical normal distribution with mean β which is the true vector of coefficients, and variance of Σ which the asymptotic variance-covariance matrix of the standard errors of the estimated coefficients, this can be seen on equation (2).

$$\hat{\beta} \sim N(\beta, \Sigma) \quad (2)$$

To standardize these vectors of estimated coefficients we first divide the Σ covariance matrix into two triangular matrixes using the Cholesky decomposition as: $\Sigma = LL'$, after obtaining the decomposition we retrieve the L matrix, and we compute its inverse (L^{-1}). Since the estimated coefficients in (2) have different standard errors and can be correlated we will

standardize them by multiplying them by the (L^{-1}) matrix.

$$\hat{\beta}^{standard} = L^{-1}\hat{\beta} \quad (3)$$

This will result in the $\hat{\beta}^{standard}$ vector seen in equation (3) which follows under an asymptotical normal distribution with the parameters seen in equation (4). Where the mean is zero and *I* stand as an identity matrix as the vector variance.

$$\hat{\beta}^{standard} \sim N(0, I) \quad (4)$$

This standardization process is conducted for two reasons, firstly we obtain a vector in which each of its components is independent and lastly these estimated coefficients are know much more reliable and convenient for testing.

(3) Market Inefficiency Magnitude (MIM)

After obtaining the vector of estimated coefficients which are now standardized, we built the magnitude of market inefficiency which can be seen in equation (5). The measure will basically consider the magnitude of the estimated coefficients so that we will start understanding if a market is characterized or not by efficiency, the ratio has the following structure:

$$MIM_t = \frac{\sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|}{1+\sum_{j=1}^{q} \left|\hat{\beta}_{j,t}^{standard}\right|} \quad (5)$$

As we can see the module is used here since we are checking if the estimated coefficients are different from zero, indeed sign does not matter because a market is inefficient whether you can predict momentum (positive coefficient) or mean reversion (negative coefficient), if absolute values were not used the measure would be netting the coefficients and overestimate a market´s efficiency. As one can see the ratio varies between zero and one, it is easy to understand that if the coefficients are not significantly different from zero which is a sign of market efficiency the ratio will approach zero, on the contrary if the coefficients have high marginal effects the ratio will be closer to 1 which is a sign of market inefficiency.

(4) Confidence Interval Construction

Although the magnitude of market inefficiency (MIM) is computed above as a straightforward interpretation and calculation there is one drawback to the ratio that will need to be corrected. Due to the use of absolute values to mitigate sign effects the ratio will be positively correlated with the number of lags used on the regression analysis, as stated on

the paper that exposed the methodology even for markets with high efficiency the MIM value can be high due to the number of lags.

To correct this the authors suggest building the confidence intervals for the MIM ratio, this is done by using a simulation approach. The objective is to get confidence intervals under the null hypothesis of $\left(\hat{\beta}^{standard} = 0\right)$ that we can then compare to the MIM values obtained.

Knowing that all $\hat{\beta}_{j,t}^{standard}$ are standard normal and knowing the correct number of lags for each regression, it allows us to build a confidence interval to be used for each regression as a function of the number of lags used on that same regression. On this work we conducted 100 000 simulations under the standard normal distribution for each $\hat{\beta}_{j,t}^{standard}$. Based on the simulated vectors we compute the MIM ratio using those vectors. Since the ratio varies between 0 and 1, we take the 95th percentile of simulated MIMs for each lag and we arrive at our confidence interval of MIM under the null hypothesis, this value will be unique for each number of lags. The confidence intervals can be found on table 24.

(5) Adjusted Market Inefficiency Magnitude (AMIM)

The last step to reach our final measure of market efficiency is to reflect on the MIM (magnitude of market inefficiency) ratio explained above the confidence intervals computed. This adjustment will pass by subtracting on both the numerator and denominator of the MIM ratio the confidence interval which has the same number of lags as the elements of the vector used to compute the MIM for each case. The AMIM ratio can be seen in equation (6).

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}} \qquad (6)$$

Since $MIM_t < 1$ the estimated of both the AMIM and the confidence interval (R_{CI}) will always be below one. However, unlike MIM which varies between 0 and 1, AMIM can be negative as well and as we shall see the interpretation of this last ratio will be even easier to interpret. Whenever $AMIM < 0$ the market is efficient and that is straightforward, that will imply that the MIM numerator will not fall within the critical region and that the null hypothesis of the EMH is not rejected. When $AMIM > 0$ this implies that the standardized estimated coefficients are higher than the confidence interval falling on the critical region violating the null hypothesis of EMH, for that number of lags. The AMIM ratio is thus much

more reliable than the MIM ratio since it corrects the mechanical relationship of the ratio with the number of lags used to compute it.

3.2. Data

The data used in this work was retrieved from two different sources. To retrieve the data since inception until 2021 for the Chinese Pilot markets the following website was used http://k.tanjiaoyi.com/. To retrieve the data for the EU ETS, China National Emission Trading Scheme and for the rest of the period up to 2023 for the Chinese Pilot Markets the following website was used https://icapcarbonaction.com/en/ets-prices. The Chinese pilot markets analysed were the following, Beijing, Chongqing, Fujian, Guangdong, Hubei, Shanghai, Shenzhen, and Tianjin. In terms of other schemes, the China National Emission Trading Scheme and the European Union Emission Trading Scheme were also analysed. The historical allowance price in each market can be observed in the Figures 1 to 10.

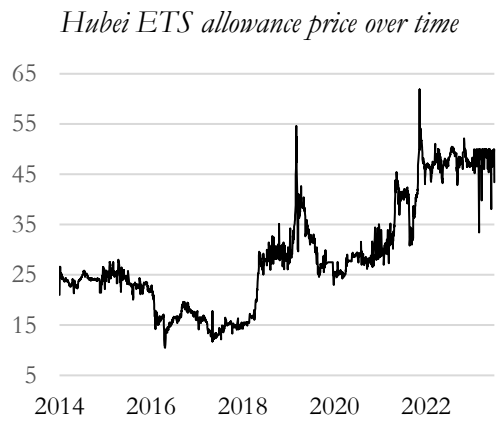


Figure 1 - Hubei ETS historical allowance prices

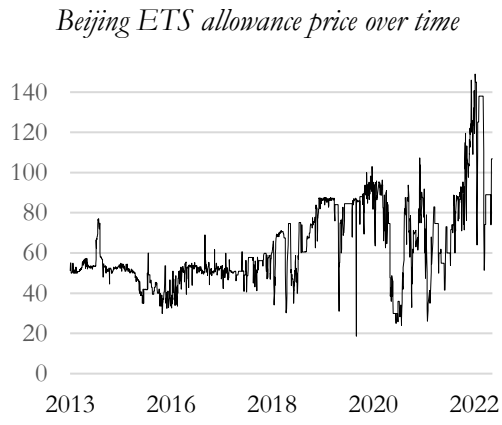


Figure 2 - Beijing ETS historical allowance prices

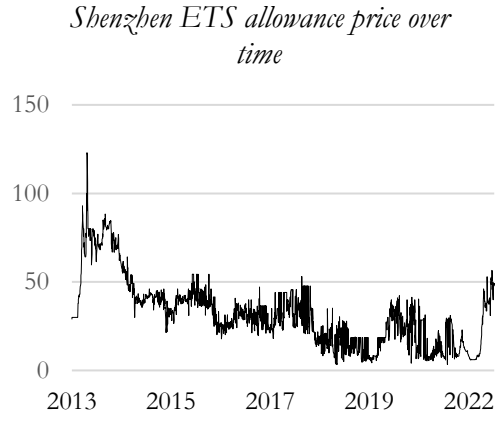


Figure 3 - Shenzhen ETS historical allowance prices

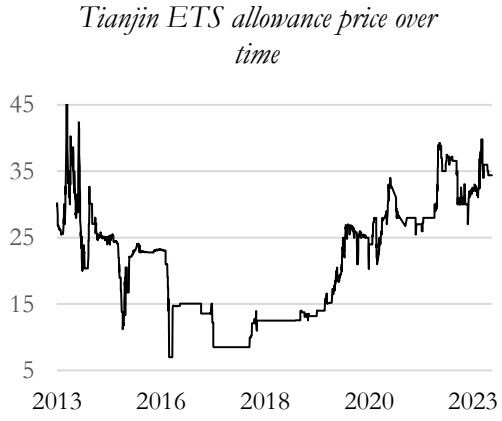


Figure 4 - Tianjin ETS historical allowance prices

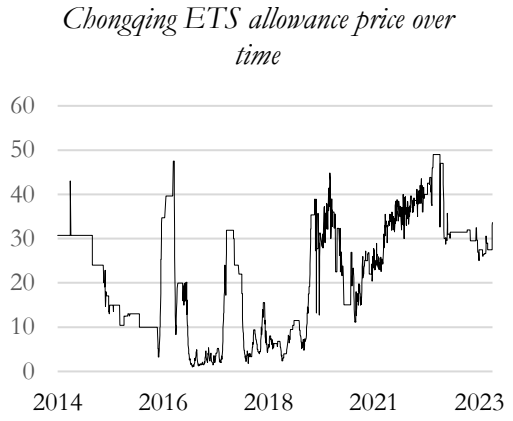


Figure 5 - Chongqing ETS historical allowance prices



Figure 6 - EU ETS historical allowance prices



Figure 7 - Guangdong ETS historical allowance prices

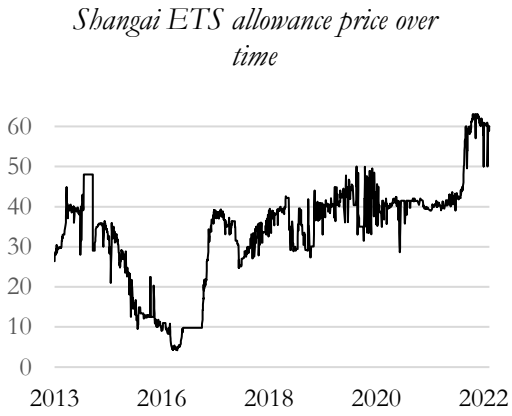


Figure 8 - Shanghai ETS historical allowance prices

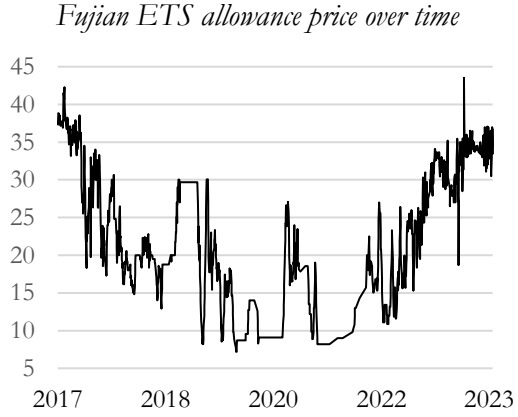


Figure 9 - Fujian ETS historical allowance prices



Figure 10 - China ETS historical allowance prices

The dataset provided on Table 1 offers a comprehensive statistical summary of the allowances returns across the 10 markets analysed in our study, including the Chinese pilot markets like Beijing, Chongqing, Tianjin, Fujian, Hubei, Guangdong, Shenzhen and Shanghai, as well as the Chinese National Emission Trading Scheme and finally the European Union Emission Trading Scheme (EU ETS). The statistics include several key measures for each market such as: the number of observations (N), Annualized return (%), Annualized Standard Deviation, maximum daily return, minimum daily return, kurtosis, and skewness.

Table 1 - Descriptive statistics

Market	N	Annualized Return (%)	Annualized Sd (%)	Max Daily Return (%)	Min Daily Return (%)	Kurtosis	Skewness
Beijing	2,360	4.06	58.0	66.8	-66.8	96.7	-0.17
Chongqing	2,220	0.45	59.9	31.4	-46.9	19.3	-0.85
Fujian	1,486	-0.2	41.7	23.4	-15.5	8.6	0.53
Guangdong	2,403	0.56	33.2	19.1	-20.2	18.7	-0.05
Hubei	2,328	3.42	27.9	17.9	-18.0	20.7	0.05
Shanghai	2,514	3.92	36.8	25.5	-25.5	24.3	0.17
Shenzhen	2,513	3.57	186.3	88.9	-93.4	14.6	-0.13
Tianjin	2,253	0.7	24.8	31.6	-30.1	152.9	0.64
China	541	7.99	13.1	4.1	-4.5	7.49	0.26
EU	4,699	4.75	80.1	303.9	-30.1	2806.5	46.6

China demonstrated the highest annualized return at 7.59%, followed closely by the EU ETS at 4.75%%. Conversely, Fujian recorded the lowest return at -0.2%. Volatility levels varied significantly, with Shenzhen exhibiting the highest volatility at 186.3% and China displaying the lowest at 13.1%.

Delving into each market individually, Beijing exhibits a moderate annualized return with a corresponding moderate level of volatility. The market's kurtosis is notably high, suggesting a potential for more extreme returns compared to a normal distribution. Chongqing shows a low annualized return alongside a moderate level of volatility. The kurtosis is relatively low, indicating a return distribution closer to a normal bell curve. Fujian presents a negative annualized return with a moderate level of volatility. The kurtosis is relatively low, like

Chongqing. Guangdong demonstrates a low annualized return coupled with a low level of volatility. The kurtosis is also low, suggesting a relatively normal return distribution. Hubei showcases a moderate annualized return with a low level of volatility. The kurtosis is moderate, indicating a return distribution somewhat closer to a normal distribution. Shanghai exhibits a moderate annualized return and a moderate level of volatility. The kurtosis is moderate, suggesting a return distribution somewhat closer to a normal distribution. Shenzhen presents a moderate annualized return but stands out with an exceptionally high level of volatility. The kurtosis is moderate, indicating a return distribution somewhat closer to a normal distribution. Tianjin displays a low annualized return with a moderate level of volatility. The kurtosis is notably high, suggesting a potential for more extreme returns compared to a normal distribution. China showcases a high annualized return with a low level of volatility. The kurtosis is moderate, indicating a return distribution somewhat closer to a normal distribution. The EU market demonstrates a high annualized return with a high level of volatility. The kurtosis is exceptionally high, indicating a significantly higher potential for extreme returns compared to a normal distribution.

These statistics provide valuable insights into the behaviour and characteristics of allowance prices returns across the different markets, highlighting variations in return levels, volatility, and distribution shapes. Such information is crucial for stakeholders and policymakers to understand market dynamics and make informed decisions in emissions trading systems; after discussing the results in our work we will attempt to make a bridge between them and these statistics.

4. Results

On this chapter we will be present the level of informational efficiency measured by the Adjusted Magnitude of Market Efficiency for the 10 markets covered in our study. Remembering the AMIM ratio when the value of this measure is above zero it means that the observed MIM value is higher than the critical region threshold at a 5% level defined by the confidence interval which is the same to say that the null hypothesis of the EMH ($\beta = 0$) is rejected suggesting that the market has an inefficient behavior. When the AMIM ratio is negative then the observed MIM value is smaller than the critical region threshold at a 5% level defined by the confidence interval which is the same to say that the null hypothesis of the EMH is not rejected being the market therefore classified as informational efficient.

Starting with the European Union Emission Trading Scheme (EU ETS), we can see the results in figures 11 and 12 as well as in Table 2.

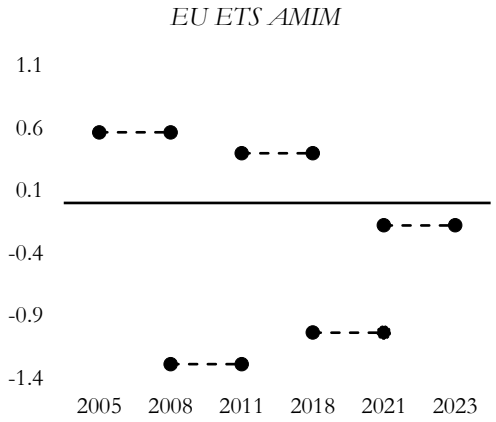


Figure 11 - EU ETS AMIM over time

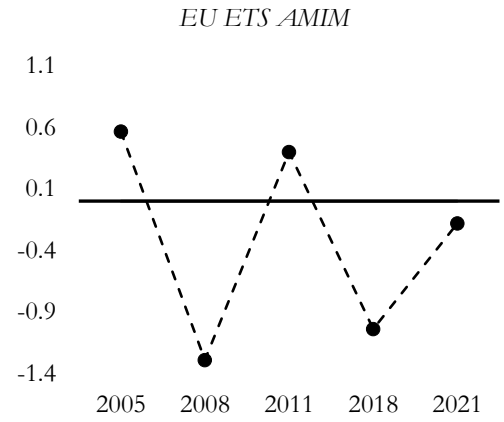


Figure 12 - EU ETS AMIM over time (linear)

Table 2 - EU ETS AMIM classification

European Union Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2005/03/10 – 2008/03/20	755	0.566	Inefficient
2008/03/25 – 2011/09/23	887	-1.291	Efficient
2011/09/26 – 2018/03/28	1649	0.398	Inefficient
2018/03/29 – 2021/01/08	705	-1.039	Efficient
2021/01/11 – 2023/10/06	704	-0.180	Efficient

The oldest ETS market, initially exhibited inefficiency near its inception but has converged towards informational efficiency over the period covered by our dataset. According to our results, the EU ETS is currently in an informationally efficient state.

The European Union Emission Trading Scheme (EU ETS) began with an AMIM value of 0.566 in the first window of estimation, indicating a moderate level of inefficiency.

In the second window, market efficiency improved dramatically, with the AMIM value decreasing to -1.289, suggesting a highly efficient market.

However, this efficiency declined in the third window, where the AMIM value increased to 0.399, indicating a return to moderate inefficiency.

In the fourth window, the market again showed significant improvement in efficiency, with an AMIM value of -1.037. The most recent window showed a slight decline in efficiency, with an AMIM value of -0.179. Despite this fluctuation, the overall trend suggests that the EU ETS has periods of high efficiency interspersed with moderate inefficiency, reflecting its dynamic nature over time.

The Adjusted Magnitude of Market Efficiency (AMIM) ratio, which is a low computational burden procedure, effectively indicates the market's efficiency across specific estimation windows rather than at each moment in time. If we assume linear convergence towards periods of efficiency and inefficiency, the scenario will resemble Figure 12. Conversely, if we account for structural breaks that impact market efficiency at a certain point in time, the reality aligns more closely with Figure 11, for all the markets analysed we will present these two figures plus an additional which for the EU ETS is Table 2. Table 2 provides a detailed view of the estimation windows for the AMIM ratio specific to the EU ETS, including the number of days or observations used in each window, the corresponding AMIM ratio values and the efficiency classification based on the measure.

Now focusing on the Chinese National Emission Trading Scheme (ETS), which is the most recent market in our study, we turn to Figures 13 and 14 as well as table 3.

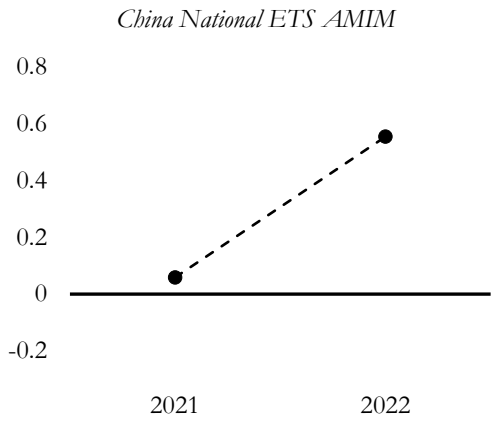


Figure 13 - China ETS AMIM over time (linear)

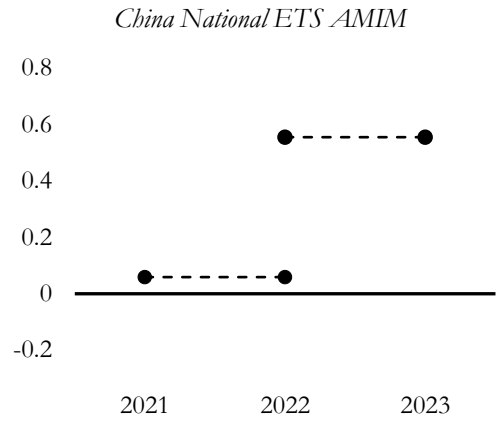


Figure 14 - China ETS AMIM over time

Table 3 - China ETS AMIM classification

China National Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2021/07/19 – 2022/12/08	340	0.059	Inefficient
2022/12/09 – 2023/09/28	202	0.555	Inefficient

It initially started with an AMIM ratio value of 0.059, as shown in Table 3 Over time, the market has experienced a decline in efficiency, with the AMIM ratio reaching 0.555 in the second window of estimation. This decrease in efficiency can be theoretically understood as a period of increased randomness near the market's inception. Early in its lifecycle, the market's immaturity and low liquidity create conditions where efficiency is initially high but diminishes as participants exploit inefficiencies. As the market evolves and matures, these inefficiencies are expected to decrease, but the initial phase reflects a natural adjustment period where the market's lack of maturity and lower degree of liquidity present opportunities for certain market participants. This phenomenon highlights the dynamic nature of market efficiency, particularly in newly established trading schemes.

Now to analyse the Chinese pilot markets, we begin by examining those currently in an informational efficiency state. The pilot markets of Tianjin which results can be seen in Figures 15, 16 and Table 4 and Beijing which results are in Figures 17, 18 and Table 5.

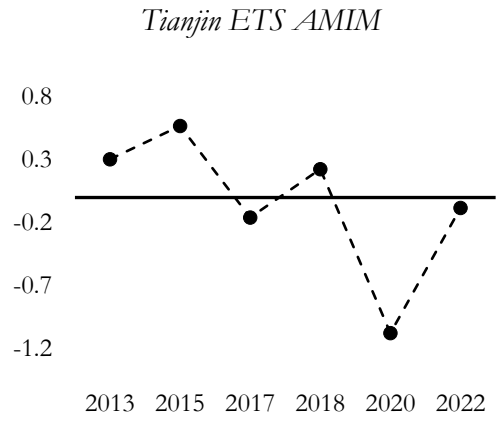


Figure 15 - Tianjin ETS AMIM over time (linear)

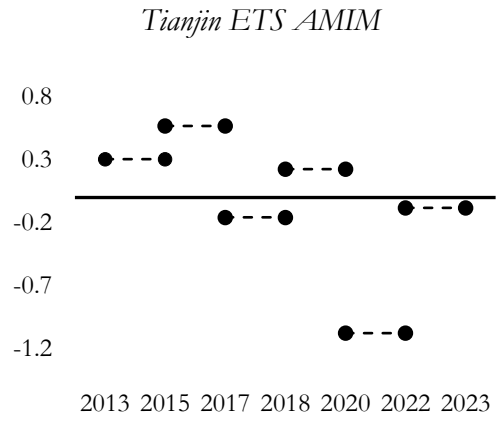


Figure 16 - Tianjin ETS AMIM over time

Table 4 - Tianjin ETS AMIM classification

Tianjin Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/12/27 – 2015/05/12	358	0.304	Inefficient
2015/05/13 – 2017/03/20	454	0.567	Inefficient
2017/03/21 – 2018/08/03	338	-0.157	Efficient
2018/08/06 – 2020/05/11	421	0.225	Inefficient
2020/05/12 – 2022/05/17	345	-1.075	Efficient
2022/05/18 – 2023/09/28	338	-0.082	Efficient

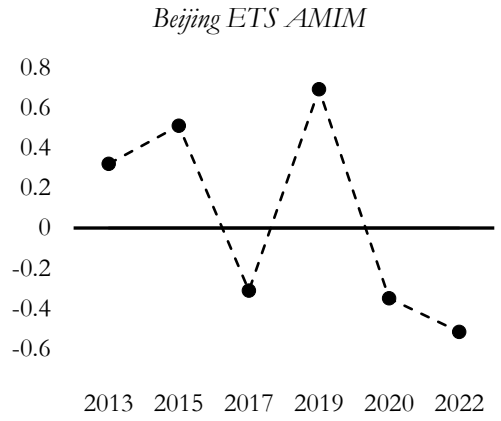


Figure 17 - Beijing ETS AMIM (linear)

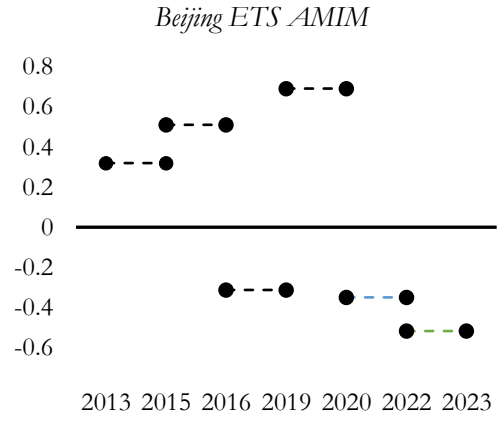


Figure 18 - Beijing ETS AMIM

Table 5 - Beijing ETS AMIM classification

Beijing Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/11/29 – 2015/04/08	354	0.320	Inefficient
2015/04/09 – 2016/09/08	354	0.511	Inefficient
2016/09/09 – 2019/02/20	591	-0.313	Efficient
2019/02/21 – 2020/08/07	354	0.692	Inefficient
2020/08/10 - 2022/04/20	354	-0.350	Efficient
2022/04/21 – 2023/09/28	354	-0.518	Efficient

Both markets were established towards the end of 2013 and initially exhibited inefficiency, with AMIM values of 0.320 for Beijing and 0.304 for Tianjin.

In the subsequent window, both markets experienced a decline in efficiency, with AMIM values increasing to 0.511 for Beijing and 0.567 for Tianjin. However, this was followed by an increase in efficiency in the third window, as evidenced by negative AMIM values of -0.313 for Beijing and -0.157 for Tianjin.

In the fourth window, both markets saw a spike in the AMIM ratio, reaching 0.692 for Beijing and 0.225 for Tianjin. This was followed by an improvement in the fifth window, where the informational efficiency of both markets improved significantly, with AMIM values of -0.350 for Beijing and -1.075 for Tianjin.

Finally, the most recent data indicates a further improvement for Beijing, with an AMIM ratio of -0.518, while Tianjin remains an efficient market with an AMIM value of -0.082. These trends illustrate the dynamic changes in market efficiency over time and highlight the progress towards greater informational efficiency in both pilot markets.

Chongqing and Guangdong have shown fluctuating levels of inefficiency, with no clear trend towards greater efficiency. The data can be seen on the figures 19, 20, 21 and 22 and on Tables 6 and 7.

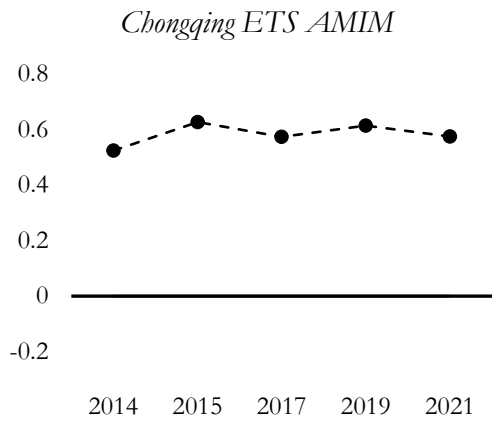


Figure 19 - Chongqing ETS AMIM over time (linear)

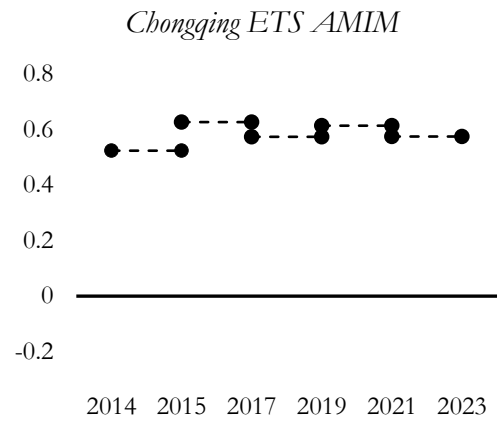


Figure 20 - Chongqing ETS AMIM over time

Table 6 - Chongqing ETS AMIM classification

Chongqing Emission Trading Scheme

Period	Days	AMIM of the Period	Efficiency Classification
2014/06/23 – 2015/10/09	333	0.524	Inefficient
2015/10/12 – 2017/03/23	355	0.627	Inefficient
2017/03/24 – 2019/10/24	629	0.574	Inefficient
2019/10/25 – 2021/06/08	386	0.614	Inefficient
2021/06/09 – 2023/09/28	518	0.575	Inefficient

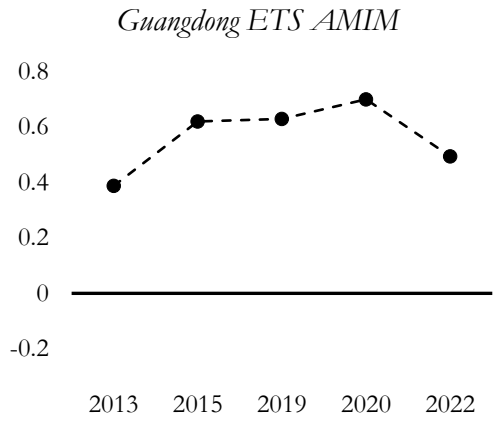


Figure 21 - Guangdong ETS AMIM over time (linear)

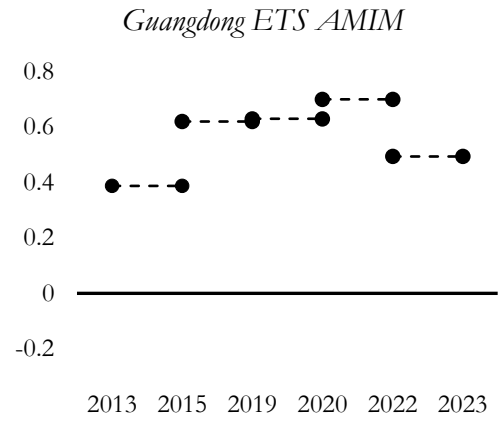


Figure 22 - Guangdong AMIM over time

Table 7 – Guangdong ETS AMIM classification

Guangdong Emission Trading Scheme			
Period	Observations	AMIM of the Period	Efficiency Classification
2013/12/20 – 2015/05/11	363	0.387	Inefficient
2015/05/12 – 2019/01/14	902	0.619	Inefficient
2019/01/15 – 2020/07/17	360	0.629	Inefficient
2020/07/20 – 2022/01/10	360	0.699	Inefficient
2022/01/11 – 2023/09/28	419	0.493	Inefficient

Fluctuation of inefficiency in both markets with no significant signs of improvement in efficiency. In both markets the value of AMIM suggesting the lower inefficiency is the one upon the first window of estimation which include the inception of the markets. These values are of 0.524 for Chongqing and of 0.387 for Guangdong. On the last window of estimation both markets remain inefficient and with the values of 0.575 for Chongqing and 0.493 for Guangdong.

Now moving to the Fujian (Figures 23, 24 and Table 8) and Hubei (Figures 25, 26 and Table 9), they show similar patterns but with some distinctions.

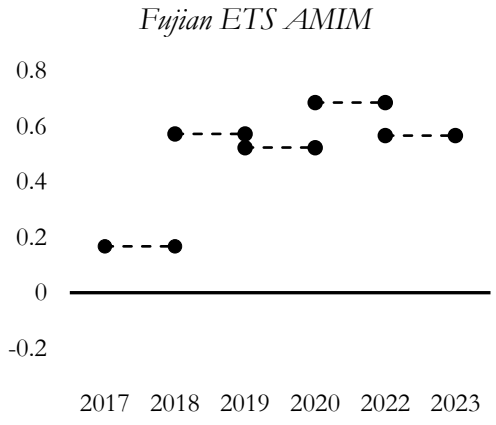


Figure 23 - Fujian AMIM over time

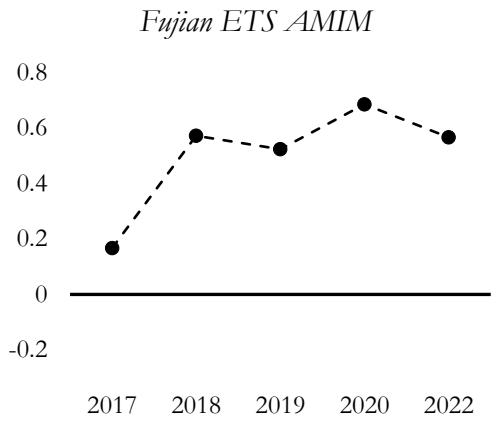


Figure 24 - Fujian ETS AMIM over time (linear)

Table 8 – Fujian ETS AMIM classification

Fujian Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2017/01/10 – 2017/12/06	223	0.167	Inefficient
2017/12/07 – 2019/07/12	387	0.572	Inefficient
2019/07/15 – 2020/07/07	233	0.523	Inefficient
2020/07/08 – 2022/08/26	378	0.685	Inefficient
2022/08/29 – 2023/09/28	266	0.566	Inefficient

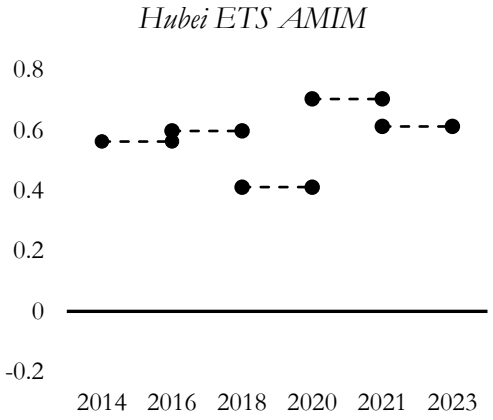


Figure 25 - Hubei ETS AMIM over time

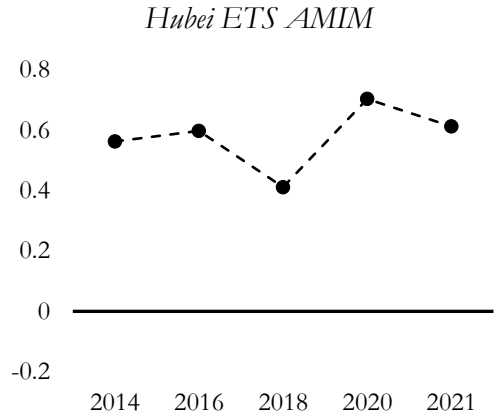


Figure 26 - Hubei ETS AMIM over time (linear)

Table 9 – Hubei ETS AMIM classification

Hubei Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2014/04/03 – 2016/04/22	522	0.563	Inefficient
2016/04/25 – 2018/07/27	553	0.598	Inefficient
2018/07/30 – 2020/01/02	349	0.412	Inefficient
2020/01/03 – 2021/07/26	374	0.704	Inefficient

2021/07/27 – 2023/09/28	531	0.613	Inefficient

Hubei has experienced both significant improvements and declines in efficiency. Shanghai started as a highly efficient market but has become less efficient over time. Shenzhen and Fujian have shown high levels of inefficiency, with recent trends indicating some improvement.

Upon inception the two ETS started with different levels of initial efficiency, as indicated by the AMIM values in their first windows of estimation. Fujian demonstrated a relatively efficient market with an AMIM value of 0.166, while Hubei began with a higher level of inefficiency, reflected in its AMIM value of 0.563.

In the rest of the windows, both Fujian and Hubei experienced fluctuations in efficiency over time. Despite these fluctuations, they shared a common trajectory of increasing inefficiency, with some periods of improvement. On th third window of estimation both markets slightly decreased their level of inefficiency to 0.412 for Hubei and 0.523 for Fujian.

The peak inefficiency of both regions occurred in the fourth window with slight differences in magnitude. Hubei reached its highest level of inefficiency with an AMIM value of 0.704, while Fujian peaked slightly lower at an AMIM value of 0.685. Despite these peaks, both regions demonstrated resilience, with minor improvements observed in their most recent window. Hubei's efficiency improved to an AMIM value of 0.614, whereas Fujian's AMIM value showed a slight uptick to 0.566.

Now moving on to Shanghai ETS we can see the results obtained in the Figures 27, 28 and in Table 10.

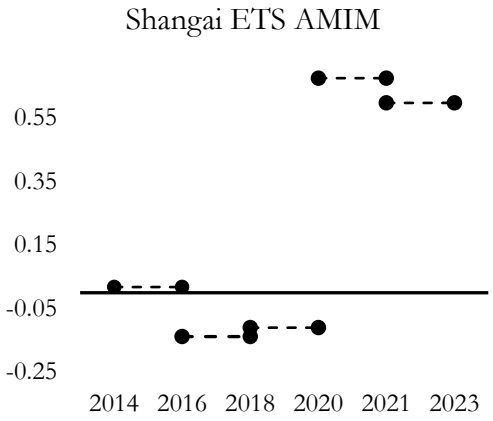


Figure 27 - Shanghai ETS AMIM over time

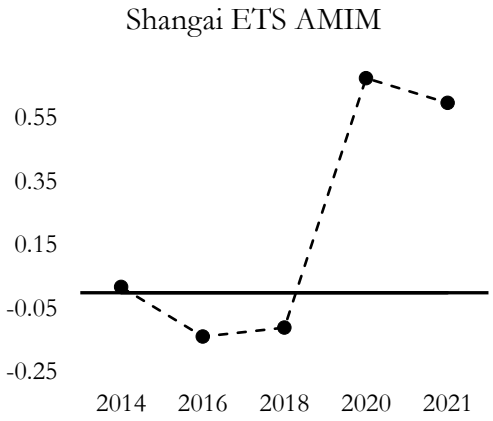


Figure 28 - Shanghai ETS AMIM over time (linear)

Table 10 – Shanghai ETS AMIM classification

Shanghai Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2014/04/03 – 2016/04/22	392	0.018	Inefficient
2016/04/25 – 2018/07/27	385	-0.138	Efficient
2018/07/30 – 2020/01/02	527	-0.110	Efficient
2020/01/03 – 2021/07/26	821	0.676	Inefficient
2021/07/27 – 2023/09/28	390	0.598	Inefficient

Shanghai ETS began with a very low AMIM value of 0.018, with a value close to suggesting the presence of an efficient market. This efficiency was achieved in the second window with a negative AMIM value of -0.138 and remained efficient in the third window with an AMIM value of -0.112. However, the fourth window showed a sharp decline in efficiency with an AMIM value of 0.676, and the fifth window saw a further decline to 0.598. Overall, Shanghai ETS started as highly efficient but has become less efficient over time.

Finally, we analysed the Shenzhen ETS which results can be found on Figures 29, 30 and Table 11.

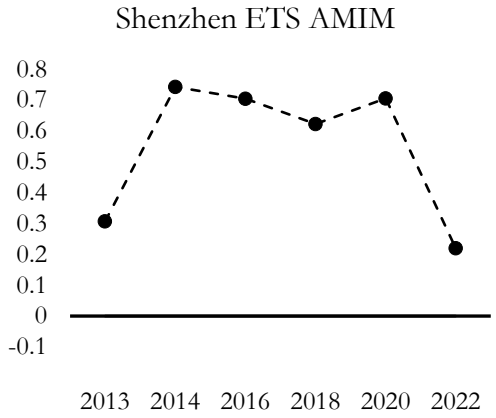


Figure 30 - Shenzhen ETS AMIM over time (linear)

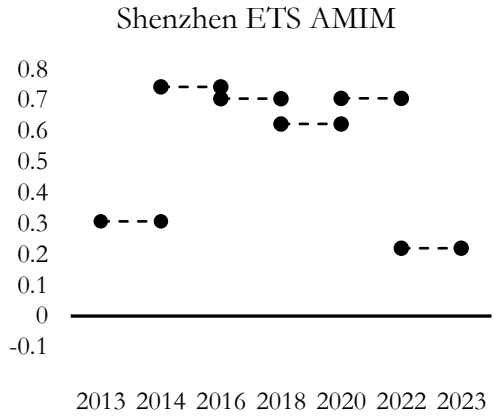


Figure 29 - Shenzhen ETS AMIM over time

Table 11 – Shenzhen ETS AMIIM classification

Shenzhen Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/06/19 – 2014/11/27	377	0.307	Inefficient
2014/11/28 – 2016/07/11	406	0.743	Inefficient
2016/07/12 – 2018/09/27	544	0.705	Inefficient
2018/09/28 – 2020/04/28	377	0.623	Inefficient
2020/04/29 - 2022/03/22	434	0.706	Inefficient
2022/03/23 – 2023/09/28	377	0.220	Inefficient

Shenzhen started with an AMIM value of 0.307, indicating moderate inefficiency. This inefficiency increased significantly in the second window to 0.742 and remained high in the third window at 0.705. The fourth window showed a slight improvement to 0.623, but the fifth window saw an increase to 0.707. The most recent window showed a substantial improvement, with the AMIM value decreasing to 0.219. Summing up the Shenzhen ETS has exhibited high levels of inefficiency with a recent trend towards improvement.

5. Discussion

5.1. EU ETS

Our findings suggest that while the EU ETS initially exhibited inefficiency, it has generally trended towards greater efficiency, albeit with periods of moderate inefficiency. Specifically, our analysis using the (AMIM) showed an initial AMIM value of 0.566, which decreased to -1.289, suggesting high efficiency. Subsequent windows showed varying levels of efficiency, with the most recent window indicating a slight decline but still an overall trend towards efficiency.

Several other studies have also examined the efficiency of the EU ETS, yielding both similar and divergent results, we will again mention some of the results achieved by previous authors and compare them to our results. To have a better understanding of the periods that our windows of estimation cover, once again, we should mention Figure 11 and 12. Montagnoli et al. (2010) explored the informational efficiency of the EU ETS during its Phase I (2005-2007) and the early part of Phase II (2008-2009). Their findings, based on unit root tests (Variance Ratio), suggested that the market was not informationally efficient in Phase I, with mixed results in Phase II. They noted that while the EMH was not supported in Phase I, it was not conclusively rejected in Phase II. This partially aligns with our findings, which also indicated inefficiency in our first window, which covered the period of 2005/03/10-2008/03/20 but showed improvements in later periods, especially on the period of Phase II (that is coincident with our second window of estimation) characterized in our study by being information efficient though with some fluctuations.

Goers (2014) also focused on Phases I and II of the EU ETS using unit root tests and autocorrelation analysis. Goers found significant autocorrelation in Phase I, indicating inefficiency, and a lack of significant autocorrelation in Phase II, suggesting an evolution towards informational efficiency. This is consistent with our results, where we observed an initial period of moderate inefficiency followed by significant improvements in efficiency, particularly in the second window of our analysis.

Another study, Daskalakis (2013) utilized a different methodology (technical analysis rules) to assess market efficiency during Phase II (2008-2012). His study indicated that technical analysis could generate substantial returns during 2008-2009, pointing to inefficiency. However, from 2010 onwards, the EU ETS showed signs of market efficiency and maturity.

This finding parallels our result; however, our results suggest that the period of 2008-2009 was already characterized by efficiency whereas in this work the author´s results suggest otherwise.

Charles et al. (2013) examined the EU ETS using the cost-of-carry model for Phase II (2009-2012). Their results suggested inefficiency, as the cost-of-carry hypothesis was rejected, indicating arbitrage opportunities. This contrasts with our findings, which suggested informational efficiency during the period analysed in this work by the authors.

Liu et al. (2021) used fuzzy entropy to analyse the informational efficiency of China's carbon markets and extended this methodology to the EU ETS. Their study found that the EU ETS was the most information-efficient market among those studied, aligning with this dissertation's results. This supports the overall trend observed in our study, where the EU ETS, despite fluctuations, shows a general progression towards greater efficiency.

5.2. Chinese Pilot Markets

As we already seen in the empirical results session of this work the results, we arrived that the Chinese Pilot Markets are mixed since we can find both efficient and inefficient, converging to efficient and non-converging to efficiency markets in our results.

When comparing our results for Tianjin, Beijing, Shenzhen, and Shanghai with the work of Zhao et al. (2017), who conducted a comprehensive study on the informational efficiency of these four pilot carbon markets in China spanning from June 18, 2013, to September 23, 2015, they concluded that the markets in Beijing, Shanghai, Shenzhen, and Tianjin had achieved weak form efficiency. This indicates that market prices reflected historical information to a degree where investors couldn't predict future prices solely based on past data. The run test results supported these findings, indicating a transition from inefficiency towards weak efficiency, attributed to market growth, higher trading volumes, improved market liquidity, and continuous enhancements in underlying market mechanisms.

In comparing our findings during the same period, we don't differentiate between weak, semi-strong, or strong forms of efficiency. We find that only the Shanghai Pilot Market can be considered efficient for this period as can be seen in figures 27 and 28. Contrary to Zhao, Wu, and Li's conclusions, our study suggests that Tianjin and Beijing's pilot markets are currently in an efficient state, indicating an overall convergence to efficiency as suggested by the authors. However, statistically concluding efficiency based on our results is not possible

for those two markets in that specific period; instead, our analysis finds efficiency in other specific periods as depicted in tables 4 and 5.

Concerning the Shenzhen market, while the period covered by Zhao, Wu, and Li's study aligns closely with the second closest to informational efficiency, our study doesn't support a conclusion of efficiency within that period, statistically speaking. Nonetheless, in our study, the Shenzhen market shows a notable proximity to efficiency in the last window of estimation, though not enough to conclusively assert efficiency.

Now, comparing our results with another study conducted by Liu et al. (2021), which analysed a data set from June 23, 2014, to June 27, 2019, we find contrasting outcomes. Liu, Jiang, and Ye concluded that the most information-efficient of China's pilot markets was Hubei, followed by Guangdong, Beijing, Shanghai, Shenzhen, Chongqing, and Tianjin. They also applied the same methodology to the EU market, finding it to be the most information-efficient of all.

In our study, during the same period, the markets closest to efficiency are Shanghai, Beijing, and Tianjin. Among these, only the Shanghai market is consistently statistically informationally efficient across most of the windows of estimation covering the period here in cause. Conversely, our analysis indicates that the Hubei, Guangdong, Shenzhen, and EU ETS markets remain inefficient throughout the entire period. Although our windows of estimation do not perfectly align with those used by Liu, Jiang, and Ye, we can apply a weighted average process using our windows of estimation and their observations to arrive at an Adjusted Market Information Measure (AMIM) that better matches the estimation window used in their study, reaching the output in table 12.

Table 12 – Readjusted windows of AMIM for the period of 2013 - 2018

Market	Period	Weighted Average AMIM of the Period
Beijing	2013/11/29 – 2019/02/20	0.084
Chongqing	2014/06/23 – 2019/10/24	0.576
Guangdong	2015/05/12 – 2019/01/14	0.552
Hubei	2014/04/03 – 2020/01/02	0.540
Shanghai	2015/06/01 – 2019/02/22	-0.080

Shenzhen	2014/11/28 – 2020/04/28	0.693
Tianjin	2013/12/27 – 2020/05/17	0.260
EU	2011/09/26 – 2018/03/28	0.398

Another study analysing the informational efficiency of China's pilot carbon markets from their inception until the end of 2017 was conducted by Yin et al. (2018). They employed a method called modified multi-scale entropy (MMSE), which involves two steps.

In the first step, they conducted a classic entropy analysis and compared the results to white noise. They concluded that all markets exhibited very low levels of efficiency, as the entropy measures were lower than those of white noise across all markets.

In the second step, they computed multiple-scale entropy. This analysis revealed that the factors driving efficiency differ between short-term and long-term scales. On shorter time scales, market efficiency is influenced by more irregular factors, leading to price fluctuations. On longer time scales, efficiency is driven by more regular factors or smooth trends.

When comparing these findings to our results, a contrast emerges. From the inception of the markets until the end of 2017, our analysis identifies several markets with windows of estimation suggesting informational efficiency. For example, the markets of Shanghai, Beijing, and Tianjin show periods of efficiency according to our results. This discrepancy highlights the importance of considering different methodologies and perspectives when evaluating market efficiency.

In the study by Liu et al. (2019)**,** a time-varying efficiency Hurst index was used to assess the maturity of China's pilot carbon markets from 2013 to 2017. They concluded that the maturity of these markets is generally low and varies across different markets. According to their results, the Hubei market exhibited the highest maturity, followed by Guangdong, Shenzhen, Beijing, Shanghai, Tianjin, with Chongqing being the least mature.

This contrasts with our findings. For the same period, our analysis identifies Shanghai as the most efficient market, followed by Beijing, Tianjin, Shenzhen, Guangdong, Hubei, and finally Chongqing. To align our evaluation periods with those used in Liu et al.'s study, we applied a weighted average process to the Adjusted Magnitude of Market Efficiency (AMIM) across our windows of estimation, the results can be seen on table 13.

Table 13 - Readjusted AMIM for the period of 2013-2017

Market	Period	Weighted Average AMIM of the Period
Beijing	2013/11/29 – 2016/09/08	0.416
Chongqing	2014/06/23 – 2017/03/23	0.577
Guangdong	2013/12/20 – 2019/01/14	0.552
Hubei	2014/04/03 – 2016/04/22	0.563
Shanghai	2013/11/27 – 2016/12/21	-0.059
Shenzhen	2013/06/19 – 2016/07/11	0.533
Tianjin	2013/12/27 – 2017/03/20	0.451

Moreover, when considering statistical significance, Shanghai is the only market that consistently respects the Efficient Market Hypothesis (EMH) throughout this period according to our windows of estimation. This discrepancy underscores the variations that can arise from different methodologies and highlights the importance of considering multiple perspectives when assessing market efficiency.

To conclude, in the study by Fan et al. (2018)**,** a Multifractal Detrended Fluctuation Analysis (MF-DFA) was used to evaluate the informational efficiency of seven of China's pilot carbon markets. They employed the Hurst exponent to gauge efficiency: a value less than 0.5 indicates a mono-fractal series, supporting the Efficient Market Hypothesis (EMH), while a value greater than 0.5 indicates multi-fractality, suggesting a violation of the EMH.

The dataset covered the period from the initiation of the Chongqing pilot market to February 9, 2018. The authors found that the Hurst exponents for each of the seven markets were greater than 0.5, indicating multi-fractality and thus a general inefficiency. However, they observed signs of growing efficiency over time, except for the Tianjin market.

These results contrast with our findings. During the same period, our analysis shows that some markets, such as Shanghai, Beijing, and Tianjin, exhibited periods of efficiency. Specifically, the Shanghai market demonstrated consistent efficiency throughout various windows of estimation. The Beijing and Tianjin markets also showed signs of efficiency at different times.

In contrast, the Shenzhen market initially showed a decline in efficiency, particularly after its inception, but gradually improved over the period. The Hubei market also exhibited a slow

but steady improvement in efficiency. However, the Chongqing and Guangdong markets showed no evident signs of improvement throughout the analysed period.

To look for answers justifying the differences in efficiency across markets and across time we will look at some factors impacting market functioning like liquidity, price level, volume, market participants, regulation among other factors.

In Huang et al. (2022) analysed the recent functioning of Chinese pilot carbon markets and the drivers of efficiency within those markets. The authors began by addressing the liquidity in these markets. Their results suggest that the level of market activity is like that of the EU ETS during the period of 2005-2007. This comparison indicates that the EU ETS was an inefficient market during that time due to a lack of liquidity. Therefore, liquidity can be seen as a major driver of market efficiency. Regulators should monitor liquidity closely and implement regulations and actions to promote higher levels of liquidity to achieve greater market efficiency.

Another important factor is the price level of carbon emissions, as discussed in the study. A higher Carbon Emission Price (CEP) corresponds to stronger emission reduction efforts, while a lower CEP may weaken the emission reduction potential of the ETS. A reasonable CEP promotes market development and reduces emission reduction costs for enterprises. Many factors influence CEP, with economic development being a significant one; higher economic activity leads to higher demand for carbon quotas and thus higher CEP.

Fluctuations in CEP are partly due to the underdeveloped market's automatic adjustment mechanisms. Incomplete Monitoring, Reporting, and Verification (MRV) systems fail to accurately reflect the supply-demand relationship and price fluctuations. Additionally, the lack of mature carbon emissions financial products prevents enterprises from effectively managing trading risks.

Based on the criteria of CEP and the fact that markets with high fluctuations tend to be less efficient, the study finds that Beijing shows a strong upward trend with high prices, indicating a robust and active market. However, the high CEP could point to inefficiencies if not managed properly. This is corroborated by our study, which suggests that the high CEP may be responsible for the AMIM value we observed for Beijing, indicating no violation of the Efficient Market Hypothesis (EMH).

Shanghai demonstrates significant improvement post-2017, suggesting an efficient response to policy adjustments. Our study confirms that during the period of 2017-2019, the Shanghai

market was indeed efficient. However, efficiency has regressed since then, which is not captured in the authors' study, as their data ends in 2020.

Shenzhen has improved over time by reducing CEP fluctuation, showing increasing efficiency as the market matured. Our study also indicates that efficiency improved during the period established by the authors.

Conversely, Chongqing and Fujian exhibit characteristics of inefficiency, with large fluctuations in CEP. Our findings align with this, showing that Chongqing has not demonstrated clear signs of efficiency improvement, and that Fujian has lost efficiency.

Now moving to Zhao et al. (2016), their study covering 2013-2014 data also analyzed price fluctuation, liquidity, and information transparency across the Chinese pilot markets.

In terms of price fluctuation, excessive price fluctuations are detrimental, making it difficult to establish a stable nationwide CET mechanism. High volatility can obscure true cost reflections and pose significant risks to market participants, negatively impacting enterprises covered by the ETS. In 2013, prices were highly volatile, but by 2014 price fluctuations decreased. However, significant differences and fluctuations remained across various ETS pilots. These results corroborate our findings, suggesting that the efficiency of many of the pilot markets is still very premature. Indeed, for the period in question, our results suggest that only the Shanghai pilot market was efficient according to our AMIM ratio.

Regarding trading volume, the authors arrived at similar conclusions. Low trading volumes and turnover, with substantial trading concentrated around submission dates, and low ratios of trading volume to carbon emission caps indicate poor market liquidity and the predominance of small transactions, particularly from individual investors, further destabilizing prices.

When mentioning liquidity, the lack of liquidity is a significant challenge across all ETS pilots in China, leading to excessive price fluctuations and small trading volumes. Intermittent deals or no deals are common phenomena, with nearly a third of trading days experiencing "having price but no deals."

Another problem presents in these markets according to the paper is the diffusion of information. Indeed, poor information transparency in China's ETS pilots poses significant challenges to market efficiency and effectiveness. Inadequate statistical systems, lack of enterprise awareness, and incomplete information services contribute to the transparency issue.

Now shifting to Xu et al. (2021), this paper tested the Chinese pilot markets for explosive behaviours by using SADF and GSADF tests to identify carbon price bubbles in eight pilot markets. This study is particularly relevant because explosive behaviours and significant deviations from fair and equilibrium prices are not characteristics of efficient markets, per example during a bubble, resources may be misallocated as investors chase inflated prices, leading to overinvestment in certain sectors or assets, furthermore persistent bubbles can undermine investor confidence in the market's integrity and efficiency, leading to reduced participation and liquidity which leads to a greater time of adjustment to equilibrium, finally markets with bubbles may send distorted price signals to market participants, making it difficult for businesses to make informed decisions about resource allocation and investment.. This misallocation can hinder economic growth and stability in the long run. Therefore, their conclusions can be used to verify the results of the methodology we employed in our analysis.

After testing explosive behaviours in the eight pilot markets, the authors emphasized several key results. Three pilots (Chongqing, Hubei, Tianjin) exhibited evidence of multiple carbon price bubbles.

In the Chongqing pilot, three bubbles were identified (2016, 2017 and 2019), occurring during distinct periods. The initial bubble was attributed to a different quota allocation method and a lack of restrictions on participants, while subsequent bubbles were linked to policy announcements and emissions inspections. In the Tianjin pilot, two relatively short-lived bubbles were observed (2015 and 2016), with limited trading days and stringent restrictions on participants contributing to market volatility. The Hubei pilot had a single bubble detected during the sample period (2018). Regarding the other markets no statistical evidence of bubbles was found.

Before discussing our results and how they complement those observed in the study, it is important to note that the absence of bubbles in a market does not necessarily imply efficiency. While bubbles are a clear indicator of inefficiency, their absence alone does not guarantee market efficiency. Other issues such as low liquidity, poor information dissemination, and market manipulation can still lead to inefficiencies in markets without bubbles. Indeed, it is suggested on the paper that many of these markets are characterized by a huge level of inactivity which is not beneficial for resource allocation.

Our results indicate that during the time covered in the study, certain markets exhibited

periods of efficiency. Specifically, the Tianjin market showed an AMIM of -0.157 from the subperiod of March 21, 2017, to August 3, 2018. The Beijing market had an AMIM of -0.313 from September 9, 2016, to February 20, 2019. Additionally, the Shanghai market demonstrated efficiency with an AMIM of -0.138 from June 21, 2015, to December 21, 2016, and an AMIM of -0.110 from December 22, 2016, to February 21, 2019.

These results indicate that the Tianjin market, at least during a subperiod of the sample used by the authors, is considered efficient according to our study. In contrast, other markets that the authors' study suggests have no market bubbles, such as Guangdong, Shenzhen, and Fujian, are considered inefficient according to our results.

Our estimation windows were based on structural breakpoints, which makes comparisons with other studies challenging. The division of the full observation period into smaller windows does not equate to the same results as estimating AMIM for the overall period. The important conclusion is that the presence of bubbles in some markets and our results both suggest that the maturity of these Chinese pilot markets is not yet fully developed, and further improvements should be encouraged.

6. Robustness' tests

To ensure the robustness of our results regarding the informational efficiency of carbon emission trading schemes, we conducted additional analyses using a fixed window approach for the estimation of the Adjusted Market Inefficiency Magnitude (AMIM) across the markets previously analysed. The approach used here differs from the method previously employed where windows were established using the Bai-Perron test for structural breaks Bai et al. (1998), allowing for the identification of the optimal breakpoints based on statistical properties. In this section, we present the differences between these two methodologies, followed by a comparison of the results obtained from the fixed window approach.

The fixed window defined covered 252 trading days for most of the markets except for the China National ETS in which the fixed window defined was one that allowed for the two windows to have the same size which does not holds for the rest of the markets since the number of observations does not allow for a perfect division. This method simplifies the analysis by providing a consistent framework to assess market efficiency, assuming that a standard duration is suitable for all markets regardless of their individual characteristics or external influences, the size of the window was defined by taking the account the standard days of trading in one year.

Starting with the EU ETS Emission Trading Scheme the fixed window approach confirmed a trend towards greater market efficiency over time. The results reached can be seen on table 14.

Table 14 - EUS ETS AMIM (fixed window)

EU ETS Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2005/03/10 – 2016/03/21	251	0.073	Inefficient
2006/03/22 – 2007/03/20	251	0.116	Inefficient
2007/03/21 – 2008/03/20	251	0.465	Inefficient
2018/03/25 – 2009/03/20	251	-1.439	Efficient
2009/03/23 – 2010/03/19	251	0.210	Inefficient
2010/03/22 – 2011/03/15	251	-0.638	Efficient
2011/03/16 – 2012/03/08	251	-0.619	Efficient

2012/03/09 – 2013/03/11	251	-0.768	Efficient
2013/03/12 – 2014/03/12	251	0.289	Inefficient
2014/03/13 – 2015/03/10	251	0.053	Inefficient
2015/03/11 – 2016/03/07	251	0.342	Inefficient
2016/03/08 – 2017/02/24	251	-1.379	Efficient
2017/02/27 – 2018/20/02	251	-0.549	Efficient
2018/02/21 – 2019/02/18	251	-0.843	Efficient
2019/02/19 – 2020/02/14	251	-1.130	Efficient
2020/02/17 – 2021/02/09	251	-0.471	Efficient
2021/02/10 – 2022/02/01	251	0.362	Inefficient
2022/02/02 – 2023/01/23	251	-0.172	Efficient
2023/01/24 – 2023/10/06	181	-0.144	Efficient

The AMIM values transitioned from positive to negative in multiple windows, however the market has generally moved towards informational efficiency which can be confirmed by its present state. This observation is consistent with the findings obtained using the Bai-Perron test which cane consulted in table 2, reinforcing the conclusion that the EU ETS has become more efficient in recent years.

For the China National Emission Trading Scheme, the fixed window approach showed a trend towards inefficiency in the early periods, with AMIM values remaining positive, results can be seen in Table 15.

Table 15 - China National ETS AMIM (fixed window)

China National Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2021/07/19 – 2022/08/26	270	-0.064	Efficient
2022/08/29 – 2023/09/28	270	0.608	Inefficient

This aligns with the results on table 3 and with the explanation provided before. The early stages of the market exhibit a random behaviour with the agents not capable on capitalizing on price movements which in the short term can they evolve to a less informational state as

specified before.

The Tianjin market displayed a mix of efficient and inefficient periods under the fixed window approach table 16.

Table 16 - Tianjin ETS AMIM (fixed window)

Tianjin Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/12/27 – 2014/12/15	251	0.256	Inefficient
2014/12/16 – 2015/12/09	251	0.111	Inefficient
2015/12/10 – 2016/12/20	251	-1.961	Efficient
2016/12/21 – 2017/12/28	251	-0.584	Efficient
2017/12/29– 2019/01/10	251	0.484	Inefficient
2019/01/11 – 2020/01/21	251	0.286	Inefficient
2020/01/22 – 2021/02/19	251	-0.088	Efficient
2021/02/22 – 2022/09/27	251	0.059	Inefficient
2022/09/28 – 2023/09/28	254	0.017	Inefficient

Several windows indicated negative AMIM values, suggesting periods of efficiency, while others showed positive AMIM values, indicating inefficiency. This results slightly differ from the ones observed on table 4 however the current state of the market under both approaches (AMIM 0.017 in the fixed widow approach and -0.082 on the Bai-perron approach) both show values close to efficiency, indeed in the former approach the market is efficient. This acknowledges the need for a precise and structural approach like the bai perron test when analysing informational efficiency state on security markets.

Now moving on to the Beijing Emission Trading Scheme, the results of the fixed window approach can be seen on table 17.

Table 17 - Beijing ETS AMIM (fixed window)

Beijing Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification

2013/11/29 – 2014/11/18	251	0.259	Inefficient
2014/11/19 – 2015/11/13	251	0.489	Inefficient
2015/11/16 – 2016/11/23	251	0.422	Inefficient
2016/11/24 – 2017/12/04	251	0.497	Inefficient
2017/12/05 – 2018/12/13	251	-0.270	Efficient
2018/12/14 – 2019/12/25	251	-0.235	Efficient
2019/12/26 – 2021/01/14	251	0.624	Inefficient
2021/01/15 – 2022/04/25	251	-0.266	Efficient
2022/04/26 – 2023/05/09	251	-0.358	Efficient
2023/05/10 – 2023/09/28	100	-0.926	Efficient

Initially, from 2013 to 2016, the market exhibited inefficiency with AMIM values exceeding zero, indicating that market prices did not fully reflect available information. However, from 2017 onwards, several windows presented negative AMIM values, suggesting a shift towards informational efficiency. This pattern aligns with the results obtained using the Bai-Perron test, which also identified periods of increased market efficiency.

For the Chongqing market, the fixed window approach confirmed persistent inefficiency over time as can be seen in table 18.

Table 18 - Chongqing ETS AMIM (fixed window)

Chongqing Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2014/06/23 – 2015/06/08	251	0.619	Inefficient
2015/06/09 – 2016/06/20	251	0.215	Inefficient
2016/06/21 – 2017/06/30	251	0.607	Inefficient
2017/07/03 – 2018/07/10	251	0.542	Inefficient
2018/07/11 – 2019/07/23	251	-0.029	Efficient
2019/07/24 – 2020/08/12	251	0.555	Inefficient
2020/08/13 – 2021/10/11	251	0.173	Inefficient
2021/10/20 – 2022/11/18	251	0.455	Inefficient
2022/11/21 – 2023/09/28	212	-0.397	Efficient

AMIM values remained consistently positive across nearly all periods, demonstrating that this market did not conform to the Efficient Market Hypothesis (EMH) throughout the years analysed. These findings are consistent with the results from the structural break method, reinforcing the conclusion that Chongqing has not achieved informational efficiency. However, the last window suggests informational efficiency with the value of -0.397 for the AMIM measure, which contradicts the results achieved in table 6.

The Guangdong market showed persistent inefficiency across all fixed windows as can be seen in table 19.

Table 19 - Guangdong ETS AMIM (fixed window)

Guangdong Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/12/20 – 2014/12/05	251	0.0529	Inefficient
2014/12/08 – 2015/12/02	251	-1.163	Efficient
2015/12/03 – 2016/12/12	251	-0.376	Efficient
2016/12/13 – 2017/12/20	251	-0.222	Efficient
2017/12/21– 2018/12/28	251	0.670	Inefficient
2019/01/02 – 2020/01/10	251	0.298	Inefficient
2020/01/13 – 2021/01/29	251	0.646	Inefficient
2021/02/01 – 2022/02/18	251	0.553	Inefficient
2022/02/21 – 2023/03/02	251	0.672	Inefficient
2023/03/03 – 2023/09/28	144	0.407	Inefficient

With AMIM values consistently remaining above zero after 2016 (first trading years) is in line with the results obtained using the Bai-Perron test, confirming that the Guangdong market has not exhibited signs of achieving informational efficiency during the periods analyses as can be seen in table 7.

The analysis of the Fujian market showed mixed results regarding its efficiency levels table 20.

Table 20 - Fujian ETS AMIM (fixed window)

Fujian Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2017/01/10 – 2018/01/17	251	0.057	Inefficient
2018/01/18 – 2019/01/30	251	-0.103	Efficient
2019/01/31 – 2020/02/25	251	0.592	Inefficient
2020/02/26 – 2021/05/18	251	0.660	Inefficient
2021/05/19 – 2022/10/24	251	0.601	Inefficient
2022/10/25 – 2023/09/28	100	0.511	Efficient

Initially, the market was inefficient; however, from 2018 to 2019, there was a brief period where AMIM values turned negative, indicating a temporary state of efficiency. As subsequent windows reverted to positive AMIM values, confirming a return to inefficiency. These findings are consistent with the structural break approach, which similarly revealed fluctuations in the market's efficiency as can be observed in table 8.

The fixed window results for the Hubei market indicated a pattern of both improvements and declines in efficiency which can be seen in table 21.

Table 21 - Hubei ETS AMIM (fixed window)

Hubei Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/04/03 – 2014/03/23	251	-0.084	Inefficient
2015/05/26 – 2016/06/01	251	0.408	Inefficient
2016/06/02 – 2017/06/15	251	-1.067	Efficient
2017/06/16 – 2018/06/25	251	0.679	Inefficient
2018/06/26– 2019/07/05	251	0.331	Inefficient
2019/07/08 – 2020/07/24	251	0.648	Inefficient
2020/07/27 – 2021/08/03	251	0.596	Inefficient
2021/08/04 – 2022/08/16	251	-0.714	Efficient
2022/08/17 – 2023/08/28	251	0.643	Inefficient

The market showed alternating periods of inefficiency and efficiency. This alternating pattern is not evidenced in table 9 by always inefficient behaviour under the Bai-Perron approach. However, since there were more windows under the fixed window approach the analysis is more granular evidencing behaviours that could not be captured in table 9. The market is still on a current inefficient state under both methods.

Shanghai's market showed a progression from initial inefficiency to moderate efficiency when analysed using fixed windows as can be seen in table 22.

Table 22 - Shanghai ETS AMIM (fixed window)

Shanghai Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/11/27 – 2014/11/13	251	0.106	Inefficient
2014/11/14 – 2015/11/10	251	0.322	Inefficient
2015/11/11 – 2016/11/18	251	0.092	Inefficient
2016/11/21 – 2017/11/28	251	0.188	Inefficient
2017/11/29– 2018/12/07	251	-1.277	Efficient
2018/12/11 – 2019/12/20	251	-1.189	Efficient
2019/12/23 – 2021/01/11	251	-0.202	Efficient
2021/01/12 – 2021/08/03	251	0.540	Inefficient
2021/08/12 – 2022/09/20	251	0.611	Inefficient
2022/09/21 – 2023/09/28	254	0.546	Inefficient

While AMIM values were negative for some periods, indicating phases of efficiency, the overall trend demonstrated that the market has undergone periods of both efficiency and inefficiency. This pattern aligns with the findings from the structural break method in table 10, which also identified changes in market behaviour over time. Under both methods the market is currently informational efficiency.

The Shenzhen market exhibited similar patterns to Shanghai, with periods of inefficiency interspersed with phases of efficiency as can be seen in table 23.

Table 23 - Shenzhen ETS AMIM (fixed window)

Shenzhen Emission Trading Scheme

Period	Observations	AMIM of the Period	Efficiency Classification
2013/06/19 – 2014/06/04	251	-1.537	Efficient
2014/06/05 – 2015/05/22	251	0.519	Inefficient
2015/05/25 – 2016/05/30	251	0.683	Inefficient
2016/05/31 – 2017/06/13	251	0.644	Inefficient
2017/06/14– 2018/06/20	251	0.641	Inefficient
2018/06/21 – 2019/07/01	251	0.600	Inefficient
2019/07/02 – 2020/07/21	251	0.627	Inefficient
2020/07/22 – 2021/08/03	251	0.623	Inefficient
2021/08/06 – 2022/09/20	251	0.617	Inefficient
2022/09/21 – 2023/09/28	254	0.653	Inefficient

The fixed window showed a market starting off with efficiency and becoming inefficient with values for the AMIM measure around 0.6. This differs from the result achieved in the approach used on the results of table 10 in which the market is efficient in the second and third window of estimation which cover the period from 2016 to 2020. This once again confirms the importance of the method selection and the use of statistical backed tests to conduct analysis.

To conclude the robustness checks using the fixed window approach largely corroborate the findings obtained through the Bai-Perron structural break method. The fixed window analysis confirms the dynamic nature of informational efficiency in carbon emission trading schemes, with some markets showing consistent improvements in efficiency over time while others remain persistently inefficient. The results of this robustness check further validate the AMIM measure as a reliable tool for evaluating market efficiency and support the conclusion that the efficiency of these markets is influenced by both market-specific factors and regulatory or policy changes.

7. Conclusion

The primary objective of this dissertation was to assess the informational efficiency of carbon ETS in both the EU and China, focusing on the EU ETS, China ETS and various Chinese pilot markets. This investigation is particularly relevant as ETSs have become essential tools in global climate policy, offering a market-based mechanism to achieve emissions reductions. Understanding the efficiency of these markets is crucial for policymakers, regulators, and investors, as efficient markets ensure that prices reflect all available information, promoting optimal resource allocation and supporting effective climate action.

The dissertation utilized data covering the EU ETS from its inception until October 10, 2023, and for China's National and pilot ETS markets from their inception until September 29, 2023. The methodology employed was the AMIM, a measure developed by Vu Le Tran et al. (2019), which is characterised by its low computational burden and straightforward interpretation of results. To dynamically determine the estimation windows for each market, the Bai-Perron test for structural breaks was applied Bai et al. (1998). This approach allowed for a more precise evaluation of market efficiency over time, taking into account structural changes in the data.

The findings of the dissertation indicate that the EU ETS, despite initial inefficiencies, has generally converged toward informational efficiency. This suggests that the EU ETS is increasingly reflecting all available information, a desirable outcome for market stability and investor confidence. On the other hand, China's National ETS and most of its pilot markets, except for Beijing and Tianjin, were found to be currently inefficient. The results indicate that while some pilot markets, such as Beijing and Tianjin, have made significant progress towards efficiency, others, including Guangdong and Chongqing, continue to exhibit substantial inefficiencies.

These findings have important policy implications. For the EU ETS, the trend toward greater efficiency suggests that its current regulatory framework, market design, and transparency measures are generally effective. However, ongoing efforts should focus on maintaining this efficiency, especially in the face of evolving market conditions and external shocks. Measures such as creating a carbon credit derivatives market, merging ETS markets within the EU, and allowing financial institutions to participate have proven effective in the EU context and could be beneficial for other markets as discussed in Kim et al. (2021). For China, the results

suggest a need for targeted policy interventions to improve market liquidity and maturity. Enhancing transparency, diversifying financial products available for trading—such as futures and options—and transitioning from free allocation to auctioning of allowances could help improve market efficiency such as suggested by Zhao et al. (2016). Policymakers may also consider implementing a market stability reserve mechanism to manage price volatility and ensure adequate liquidity.

From an investor's perspective, the findings highlight different risk profiles and opportunities across these markets. The relatively high efficiency of the EU ETS implies a lower likelihood of arbitrage opportunities but greater price stability, making it an attractive option for long-term investments Kim et al. (2021). In contrast, the inefficiencies observed in China's markets suggest potential for arbitrage and short-term gains, but they also indicate higher risks and uncertainty. Recommendations for China include enhancing supervision systems to monitor trading volumes accurately, introducing financial products to manage risks, and implementing policies to reduce volatility and encourage continuous trading as suggested by Huang et al. (2022). Moreover, creating robust legal frameworks, reward and punishment mechanisms, and environmental information transmission networks could further stabilize prices and promote market activity as supported by Xu et al. (2021).

These insights also contribute to the broader debate on market efficiency and the EMH in the context of emission trading schemes. The results suggest that while the EU ETS has evolved towards efficiency, indicating its capacity to reflect all available information, the Chinese markets are at different stages of development and efficiency. This raises questions about the general applicability of the EMH in emerging carbon markets and points to the need for further research into the unique characteristics of these markets.

Despite its contributions, this dissertation has several limitations. First, the data is limited to a specific period, and longer-term analyses could provide a more comprehensive understanding of market efficiency trends. Second, the study focuses solely on the informational efficiency of the markets without considering other factors, such as participant behavior, which might influence efficiency. Future research could extend the scope by exploring these additional dimensions or by applying the AMIM measure to other emerging carbon markets worldwide.

In conclusion, while significant progress has been made in understanding the informational efficiency of carbon markets, much remains to be explored. This dissertation provides a

foundation for further investigations, emphasizing the need for continuous monitoring and evaluation to ensure that these critical tools in the fight against climate change operate effectively and efficiently.

Appendix

Table 24 - Confidence intervals for the AMIM measure

Number of lags	95% CI	Number of lags	95% CI
1	0.662255611	16	0.944143745
2	0.760181957	17	0.946839294
3	0.810572652	18	0.949333880
4	0.842221646	19	0.951510430
5	0.864270993	20	0.953709043
6	0.880531801	21	0.955518547
7	0.893357897	22	0.957172169
8	0.903689147	23	0.958873609
9	0.911787502	24	0.960219042
10	0.918532398	25	0.961656261
11	0.924446311	26	0.962877216
12	0.929505422	27	0.964145560
13	0.933921789	28	0.965197614
14	0.937651094	29	0.966259015
15	0.941075174	30	0.967279436

The upper bound 95% Confidence Intervals (CI) under the null hypothesis of efficiency market for MIM, where: $MIM_t = \frac{\sum_{j=1}^{q}\left|\hat{\beta}_{j,t}^{standard}\right|}{1+\sum_{j=1}^{q}\left|\hat{\beta}_{j,t}^{standard}\right|}$ with different number of lags in the Eq. (1). The lower bound of this interval is 0. To compute CI, we first simulate 100 000 observations for each, following a standard normal distribution. Then based on these $\hat{\beta}_{j,t}^{standard}$, we compute MIM. For each number of lags, we have 100 000 observations MIM under the null hypothesis of market efficiency. After that, we find the 95th % quantile of MIM. So, the interval between this 95th % quantile and 0 is the 95% confidence interval of MIM under the null hypothesis.

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