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Cum-Fake Trading Using ADRs from European Countries

An event study of all European ADRs

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Abstract

In this thesis, we investigate the use of European ADRs in cum-fake schemes. We look at the daily trading volume for all ADRs for European companies in the longest possible time span for each company, with the longest being 1984 to 2022. Cum-fake, cum-cum and cum-ex schemes have collectively resulted in huge funds being heisted from European governments and tax authorities in recent years. The cum-fake scheme involves exploiting pre-released ADRs to receive a tax refund on withholding tax that has never been paid.

Our analysis is divided into two parts. First, we look at the daily trading volume around the ex-dividend date on a country-by-country basis, with the purpose of finding which European countries have been affected by cum-fake trading. Secondly, we take these countries and use the daily deviation from the yearly average of each company to find the years for each country that show clear signs of cum-fake trading.

We find that there are several countries that show significant relations between the trading volume and the ex-dividend date. However, the estimated abnormal volume is lower than expected. In the yearly analysis, we find that the 1990s seems to be the most prevalent period for cum-fake trading.

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1 Introduction

The cum-ex scandal is a financial scandal that has been uncovered in Europe in recent years. It revolves around taking advantage of tax loopholes that allow financial institutions and their clients to receive multiple tax refunds on a single dividend pay-out. It is a complex scheme where the goal is to obscure the real recipient of the dividend, allowing for multiple tax refund applications on each dividend. This has resulted in billions of euros in losses for European governments and taxpayers (European Securities and Markets Authority, 2020)

The cum-ex scandal first came to light in Germany. It was later revealed that similar schemes had also been used in other European countries such as France, Spain, Belgium, and Denmark (Spengel, 2021a). It is estimated that the total amount of money lost due to cum-ex trading could be as high as $60 billion (Brogaard & Rösch, 2023).

After the scandal broke, governments in Europe began to crack down on the tax loophole and launched investigations into the financial institutions involved with the scheme. As a direct consequence, laws and systems were reformed to combat the possibility of cum-ex trading in the future. The cum-ex scandal highlighted the need for tighter regulations in the financial sector and the importance of cooperation between European countries to combat financial crimes. It also raised questions about the ethical implications of using such tax loopholes and the responsibilities of financial institutions in preventing and reporting such activities.

The cum-ex scheme is not alone though as there has also been found evidence of similar cum-cum and cum-fake schemes. The cum-fake scheme is what we investigate further in this thesis. An important part of the cum-fake scheme is the use of pre-released American Depository Receipts (ADRs). Usually, ADRs are a perfectly legal way to trade European stocks in the US, as they are negotiable certificates that follow the price and characteristics of the underlying stock. A bank in the country of origin purchases a stock and puts it in their vault for safekeeping, while at the same time issuing an ADR of the same value in the US. The cum-fake scheme has sprung out from the depositary banks pre-releasing these ADRs, to be used for tax arbitration purposes.

Several institutions and private persons have been investigated and convicted for the misuse of pre-released ADRs. Banks like JPMorgan, Deutsche Bank and Citibank have all been ordered to pay fines of up to $135 million each (Securities and Exchange Commission, 2018c). Not only depository banks have been found guilty. Several brokers like BMO and Merrill Lynch as well as four individuals have been found guilty and ordered to pay fines. The total amount of settlements amount to just over $432 million (Securities and Exchange Commission, n.d.).

While the fines given by the SEC add up to a hefty sum, it is far from the estimated $60 billion that has been looted from European governments and taxpayers. With the cum-fake scheme leaning heavily on ADRs, we theorize that looking at the trading volume for ADRs can identify cum-fake trading to some extent. This is backed by previous literature as Spengel (2021a) finds strong trading volume peaks of ADRs around dividend dates in companies from multiple European countries.

Our aim is to expand on these findings by looking at the trade volume for all European ADRs over the largest time-period possible. The research question we have chosen is to investigate in which European countries there have been cum-fake trading, and can we identify when it has been used most prevalently? Our ambition is that the findings give a clear picture of where and when cum-fake transactions have taken place. We believe this can further expand the field of cum-ex and cum-fake knowledge and be used for future researchers to utilize data from the right countries and time periods.

Our research question is focused on countries and time. Therefore, we first separate the data by country so we can do the analyses on a country-by-country basis. Our results are based on estimates from running fixed-effect regressions on the connection between country and the trading volume on the ex-dividend date and surrounding days. For the second part of the analysis, we continue with the countries that showed significant signs of cum-fake trading. We then look at the relationship between trading volume in a given dividend period and the yearly average. Another regression gives us the yearly estimates of this relationship in each country.

Our contribution to the cum-fake research is an overview of which European countries have seen cum-fake trading as well as the most significant time periods for those countries. What differentiates our study from previous literature is the scope we have chosen. We look at the

longest possible timeframe and include all European companies who currently or previously have issued ADRs. As far as we know, this has not been done before. It is due to this choice that we find evidence that suggests cum-fake trading was at its highest in the 1990s. Which is, to our knowledge, an unexplored era within this topic.

The thesis consists of five main chapters, where this introduction serves as the initial one. In the second chapter, we delve further into the theoretical framework upon which this thesis is constructed. This includes background information and explanations of procedures and concepts that is used and referenced throughout the thesis. The third chapter presents the methodology, including our objectives, data collection and descriptive statistics. The results of the analyses are shown both graphically and descriptive in the fourth chapter. Finally, we present our conclusions in the fifth chapter.

2 Theoretical Framework

This chapter consists of the theoretical framework which our research is built upon. First, we look at previous literature within this and adjacent fields that we believe are relevant for our thesis. We then look at the different theoretical concepts and procedures involved in our research and explain how they work and their role in the analysis.

Our thesis focuses on observing cum-fake trading involving American Depository Receipts (ADRs). Therefore, we begin by providing a description of what ADRs are and how they function. We then touch in on the concept of pre-released ADRs and how it has been misused. The cum-fake scheme is a tax arbitration scheme that is based on exploiting loopholes around the withholding tax on dividends. Therefore, we look into both how the withholding tax and the dividend distribution works. Lastly, we explain the complex procedures of the cum-fake scheme. We also include explanations of the cum-cum scheme and the cum-ex scheme as they share many of the same attributes.

2.1 Literature Review

In this section we provide literature that is relevant for our thesis. The literature on pre-released ADRs and cum-fake trading is limited. However, literature on similar dividend arbitrage methods such as cum-ex trading may be relevant for our thesis.

Buettner et al. (2020) studies withholding tax non-compliance with regards to dividend taxation. More specifically, their study focuses on identifying the presence of cum-ex transactions involving German stocks. They find that the trading volume increases significantly before the ex-dividend day for stocks with taxable dividends. Additionally, there were no indications of change in the market price. They point out that this is a biproduct of the fact that the parties in a cum-ex transaction must collude for it to be profitable. The study examines the period from 2009 to 2015. They find that after the dividend taxation reform in January 2012, the increase before ex-dividend day is significantly lower.

The studies by Buettner et al. use data from German stocks instead of ADRs. Nevertheless, their findings can be useful. Since there are great similarities between cum-ex and cum-fake transaction, we expect to see similar tendencies in our research.

Spengel (2021b) addresses the European Parliament on the cum-ex/cum-cum Scandal in Germany. He states that even after the tax reform in 2012, it is still possible to achieve multiple refunds even though the dividend withholding tax is paid only once. Moreover, the study identifies two mechanisms that allows for multiple tax refunds in situations where no taxes have been paid. The first method is a more complex variant of cum-ex. The latter is cum-fake transactions using pre-released ADRs.

Spengel (2021a) estimates the fraudulent tax reclaims caused by Cum-Ex – ADR transactions. The study examines the period between 2000 and 2020 on nine European countries. Spengel tests whether there is abnormal trading volume in a ten-day window around the dividend payment day. He identifies abnormal trading volume in six of the countries between 2009 and 2020. He assumes that this is likely connected to cum-ex activities. Based on these numbers, Spengel estimates the tax damage to be around USD 647 million.

Casi et al. (2022) studies the effect of the Danish reform aimed at preventing dividend-withholding tax arbitrage around dividend payment dates. They compare Denmark to its Nordic neighbours. The study focuses on the cum-cum and cum-ex schemes. They find spikes in security lending volume in countries that levy a dividend withholding tax. These spikes are also reflected in the transaction volume of a stock, thereby corroborating the findings of Spengel (2021a) and Buettner et al. (2020). In addition, Casi et al. (2022) finds evidence that spikes in security lending volume disappears or strongly declines after the introduction of a tax reform. Although our thesis does not directly investigate the effects of tax reforms, it is important to acknowledge that they can potentially serve as an explanatory factor if we observe decreases in trading volume coinciding with these reforms.

Wagner and Wei (2022) analyse the extent of cum-ex trading in European markets. They conduct tests to determine whether the abnormal trading volume observed around the ex-dividend date can be attributed to cum-ex trading. They also consider alternative hypotheses to explain the excess volume, such as investors' tax preferences and heterogeneity, risk factors, and transaction costs. They find evidence that the abnormal trading volume around ex-dividend dates are associated with cum-ex trading. This corroborates literature that have found abnormal trading volume around ex-dividend dates, supporting that the observed abnormalities originate from cum-ex transactions.

From previous literature it seems that there is a consensus that abnormal trading volume around ex-dividend dates is connected to fraudulent cum-ex transactions. On the other hand, existing literature on cum-fake transactions are limited. Most of the mentioned literature involves transactions with common stocks instead of ADRs. However, as seen in figure 4 and 5, there are similarities between cum-ex and cum-fake transactions. We assume that some of the existing findings on the former are applicable to cum-fake transactions as well.

The similarity between the previously mentioned studies is that they focus on a relatively narrow time period. We aim to expand on the existing literature by studying fraudulent pre-released ADR transactions over a significantly longer time period. As stated in section 2.3, once pre-released ADRs are issued, they are indistinguishable from ordinary ADRs. This implies that we are not be able to find direct evidence of cum-fake transactions. We only have the opportunity to find indirect evidence, i.e., abnormal trading volume around the ex-dividend date.

2.2 American Depositary Receipts

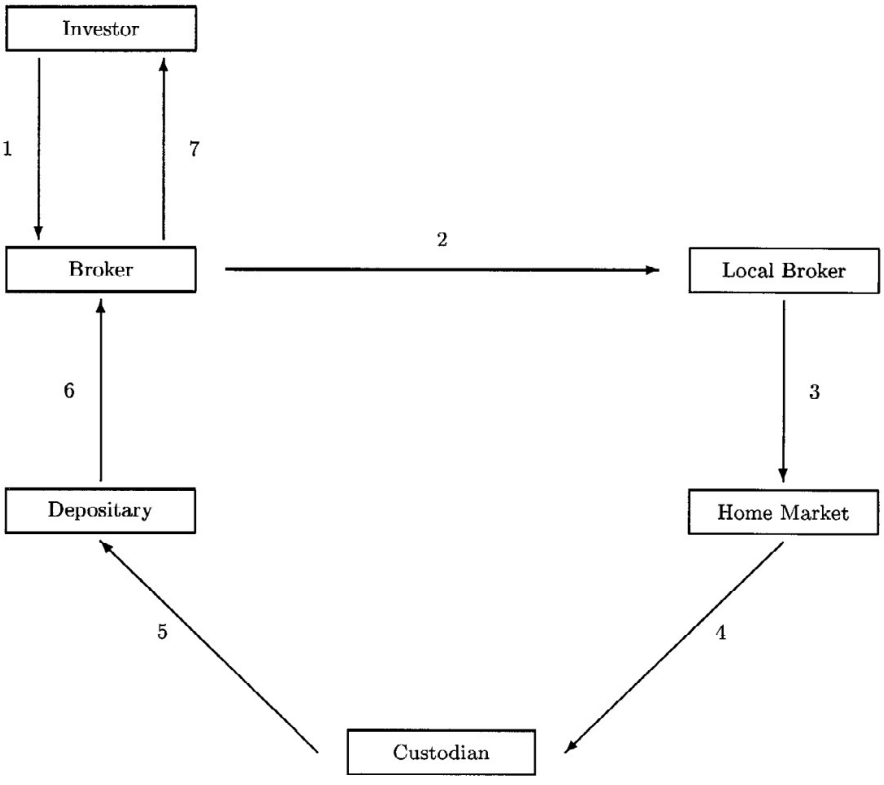
American depositary receipts are negotiable certificates that represents ownership of stocks in foreign companies. They were first introduced in 1927 with the aim to streamline the process for U.S. investors to trade foreign stocks, and they have since become a valuable tool for both U.S. and foreign investors. ADRs simplify the process of investing in foreign companies for U.S. investors. In addition, they offer foreign companies an avenue to raise capital from U.S. investors without having to list their firms on a U.S. stock exchange (Hayes, 2022). The use of ADRs has grown significantly since its introduction. Today there are over 2000 at investors' disposal that represents shares of companies from over 70 countries (Securities and Exchange Commission, 2012).

Depending on the company, ADRs may represent the underlying shares on a one-to-one basis or as a fraction of a share or multiple shares. For example, an ADR for a particular company could represent several shares of the underlying security, while for another company, an ADR may only represent a fraction of a share. The use of a ratio enables ADRs to be priced more in line with typical U.S. market share prices, thereby making them more accessible to U.S. investors (Securities and Exchange Commission, 2012).

Figure 1 displays the multi-step process that takes place in the creation of ADRs. The process starts with an investor that reaches out to their broker with a request to buy a company's ADR. If there are no existing ADRs in the U.S. stock market the broker needs to contact a local broker in the company's home market in order to have an ADR created. The broker in the home market buys ordinary shares of the stock. The shares are deposited with a custodian in the home market. The custodian then informs the depositary that they have received the underlying shares and instructs them to issue ADRs that represents the shares received. Finally, the depositary issues the ADRs and deliver them to the investor's broker which then deliver them to the investor (Gande, 2001).

When the issuance of ADRs takes place, this can happen either as a sponsored or an unsponsored program. Under a sponsored program, ADRs are issued by a depositary that has been appointed by the foreign company. In contrast, an unsponsored program is issued without an agreement between the depositary and the foreign company and are a response to the market demand (Gande, 2001).

Figure 1: Creation of American Depositary Receipts



Source: (Gande, 2001)

2.3 Pre-released American Depositary Receipts

Pre-released ADRs and ordinary ADRs are virtually identical. However, only the pre-released ADRs can be used in the cum-fake schemes we investigate. The primary difference is that in the case of pre-released ADRs, the underlying shares of stock have not yet been deposited with the custodian bank. They have been developed to address processing delays due to technical reasons and enable trading in ADRs during the period until the original shares are deposited. This is particularly relevant in the case of new issues, where the issue date and settlement day may be several days apart. The use of pre-released ADRs bridges this gap, enabling investors to trade in ADRs during this period (Lenz, 2019). When a pre-released ADR is issued it can be traded freely and cannot be distinguished from an ordinary ADR (Securities and Exchange Commission, 2017c).

For a pre-released ADR transaction to take place there must be a ‘’Pre-release Agreement’’ between the brokers and the depositaries. The broker or its customer that will receive the pre-released ADR are required by the agreement to own the underlying shares of the ADRs. In addition, they must assign all beneficial rights, titles, and interests in the underlying shares to the depositary during the period in which the pre-release transaction is outstanding. This means that the broker or its customer works as a temporary custodian of the underlying shares that would have been delivered to a custodian (Securities and Exchange Commission, 2017c).

2.4 Misuse of Pre-Released ADRs

Starting from early 2017, the U.S. Securities and Exchange Commission (SEC) has made a series of enforcement actions targeting the misuse of pre-released ADRs. The SEC is a U.S. federal regulatory agency responsible for overseeing securities trading. To this date, 15 depositary banks and brokers have been convicted and fined for improper handling of pre-released ADRs. The SEC has also charged four individuals as part of the enforcement. Table 1 presents the convicted entities and the corresponding settlements. The total settlements, including those for the individuals, amount to just over $432 million.

Among the convicted entities, JPMorgan Chase Bank received the highest monetary settlements. In its investigation, the SEC determined that JPMorgan Chase Bank had repeatedly neglected to verify whether the pre-release broker or its customer possessed the

underlying shares. This lack of verification resulted in the issuance of ADRs that were not adequately backed by the underlying shares (Securities and Exchange Commission, 2018d).

The SEC found that JPMorgan had thousands of pre-release transactions that remained outstanding for extended periods, which could not be explained by settlement timing. From Nov. 2011 to mid-2014, JPMorgan had 14 600 pre-release transactions outstanding. Out of those, more than 7,000 remained outstanding for a period exceeding 5 days, over 1,300 were outstanding for more than 30 days, and over 400 were outstanding for more than 100 days. The SEC also found that the transactions were mostly closed by the pre-released ADRs being delivered back to JPMorgan instead of the ordinary shares being delivered to the custodian. Due to the number of long-lasting transactions and the way they were closed, the SEC found that JPMorgan should have recognized that the pre-released ADRs were used improperly (Securities and Exchange Commission, 2018d). BNY Mellon, Citibank and Deutsche Bank Trust Company Americas were convicted of the same conduct.

The convicted brokers can be broadly categorized into two groups: pre-release brokers who directly obtained pre-released ADRs from depositary banks, and brokers who obtained the pre-released ADRs from other pre-release brokers.

The SEC found that the pre-release brokers who obtained pre-released ADRs from the depositary banks lent them out to other parties without verifying that they were backed by ordinary shares. For instance, Banca IMI Securities Corp., one of the convicted brokers, did not have ownership of ordinary shares in any of the pre-release transactions. Furthermore, they also failed to verify whether the parties to whom they lent the shares possessed the underlying shares (Securities and Exchange Commission, 2017b).

Merrill Lynch, Pierce, Fenner & Smith Incorporated (Merrill) obtained pre-released ADRs from pre-release brokers that had received them from depositary banks. Similar to the cases with the depositary banks and brokers, the SEC found that Merrill had not taken reasonable steps to verify that the pre-released ADRs were backed by ordinary shares. Furthermore, they found that Merrill had profited by lending the ADRs to non-U.S. parties with tax-favoured status in a foreign jurisdiction. This arrangement allowed the non-U.S. party to receive a greater portion of the dividend compared to a standard U.S. taxpayer who would be subject to foreign withholding tax. The non-U.S. party would borrow the ADRs from Merrill at a cost

equal to a certain percentage of the foreign tax benefit they would receive (Securities and Exchange Commission, 2019f).

The convicted individuals all had a prominent role with regards to pre-released ADRs. Furthermore, they all had affiliations with one of the convicted brokers. Anthony Portelli and Domenick Migliorato were both directly responsible for supervising security lending desks within their respective companies. The SEC found that both knew that securities lending personnel obtained pre-released ADRs without them being backed by ordinary shares (Securities and Exchange Commission, 2017a; Securities and Exchange Commission, 2019c). In the cases involving Wendy Katz and Melanie Ryan the SEC found similar conducts, with both individuals neglecting to verify if the pre-released ADRs were backed by ordinary shares (Securities and Exchange Commission, 2018e; Securities and Exchange Commission, 2019h).

The common denominator in the orders by the SEC is that the convicted entities had knowledge about the misconduct that was being committed. This displays an atmosphere of unculture in the sector, where unethical behaviour and dishonesty were tolerated. It is also notable that the only convicted entities are depositary banks, brokers and individuals that are responsible for lending out the pre-released ADRs. To our knowledge, there has not been any enforcement actions made against foreign entities receiving the ADRs.

Table 1: List of enforcements and total settlements

Depositary Banks	**Date**	**Total Settlements**
BNY Mellon	Dec. 17, 2018	$ 54 187 553
Citibank	Nov. 7, 2018	$ 38 750 260
Deutsche Bank Trust Company Americas	July 20, 2018	$ 73 284 828
JPMorgan Chase Bank	Dec. 26, 2018	$ 135 177 679
Brokers		
ABN AMRO Clearing Chicago	Feb. 6, 2020	$ 586 420
Banca IMI Securities Corp.	Aug. 18, 2017	$ 35 411 021
BMO Capital Markets Corp.	Aug. 16. 2019	$ 3 964 703
Cantor Fitzgerald & Co.	Aug. 16, 2019	$ 647 911
Deutsche Bank Securities	July 20, 2018	$ 1 648 266
Industrial and Commercial Bank of China Financial Services	June 14, 2019	$ 42 835 192
ITG	Jan. 12, 2017	$ 24 450 468
Jefferies	Dec. 9, 2019	$ 3 995 540
Merrill Lynch, Pierce, Fenner	March 22, 2019	$ 8 064 476
SG Americas Securities	Sept. 25, 2018	$ 819 329
Wedbush Securities	June 18, 2019	$ 8 109 249
Individuals		
Wendy Katz	Aug. 29, 2019	$ 20 000
Domenick Migliorato	Oct. 15, 2019	$ 150 000
Anthony Portelli	June 22, 2017	$ 100 000
Melanie Ryan	July 24, 2018	$ 10 000
	TOTAL	$ 432 212 898

Source: (Securities and Exchange Commission, 2017a-c, 2018a-g, 2019a-h, 2020)

2.5 Withholding Tax

The concept of withholding tax implies that employers deduct tax on behalf of the government. This is often associated with salary payments where the tax is deducted from the gross wages and paid directly to the government. The amount that is held back is set. If the amount of tax withheld is insufficient, the employee needs to pay the remaining tax owed to the government. Conversely, if the amount of tax withheld is excessive, the employee may be eligible for a tax refund. The purpose of this practice is to tax at the source instead of collecting tax after it has been earned (Kagan, 2022).

Taxation of dividends on ADRs works in a similar manner. Most European countries withhold tax on dividends paid out to foreign investors. At the same time, U.S. investors are obliged to report and pay U.S. income tax on all income received from abroad (U.S. Department of the Treasury. IRS, 2022). Table 2 presents the withholding tax rates as of 2022 for each country that are included in our thesis. The rates vary significantly across different countries, as evident from the data. Some countries, such as Switzerland, impose the highest withholding tax rates of up to 35%, while others do not levy this tax at all.

The fact that U.S. investors are subject to tax in both the U.S. and the foreign country introduces the possibility of double taxation. Certainly, such an outcome would impose a heavy tax burden on investors and could potentially diminish the incentives for investing overseas. To avoid double taxation, the U.S. provides investors with the option to claim a tax credit for foreign taxes paid. Additionally, they have entered into tax treaties with multiple countries (Internal Revenue Service, 2023a; Internal Revenue Service, 2023b). The tax treaties dictate a maximum rate of tax that can be withheld on dividends. As evident from table 2 and 3, this rate is often lower than the standard withholding tax in the foreign country. The investor can claim a credit for the tax paid up to the limit specified in the tax treaty.

In a standard ADR transaction, the sub-custodian, residing in the same country as the public company from which the ADRs originate, retains the difference between the gross and net dividends. This is carried out in accordance with the arrangements of the double taxation agreement between the United States and the home country of the public company (Lenz, 2019). For instance, an investor who buys an ADR of a company located in Belgium would be

subject to a tax of 15%. In a pre-release ADR transaction this is not always the case, as evident in section 2.7.3 and 2.7.4.

Table 2: Withholding Tax Rates of the Countries Included in our thesis

Country	**Tax rate**
Austria	25%
Belgium	30%
Denmark	27%
Finland	20%
France	25%
Germany	25%
Greece	5%
Hungary	0%
Ireland	25%
Italy	26%
Luxembourg	15%
Netherlands	15%
Norway	25%
Portugal	25%
Spain	19%
Sweden	30%
Switzerland	35%
Turkey	15%
United Kingdom	0%

Source: (Organisation for Economic Co-Operation and Development, 2023)

Table 3: Dividend withholding tax treaty rates

Country	**Tax treaty rates**
Austria	15%
Belgium	15%
Denmark	15%
Finland	15%
France	15%
Germany	15%
Greece	0%
Hungary	15%
Ireland	15%
Italy	15%
Luxembourg	15%
Netherlands	15%
Norway	15%
Portugal	15%
Spain	15%
Sweden	15%
Switzerland	15%
Turkey	20%
United Kingdom	15%

Source: (Deloitte, 2023)

2.6 Distribution of Dividends

A dividend is a portion of a company's profits that is paid out to its shareholders, usually on a regular basis like quarterly or annually. This is a means for a company to share its profits with its investors. The process of companies paying out dividends can be divided into four steps as illustrated in the figure below.

Declaration date is the date of which a company declares that a dividend should be paid out to shareholders. Typically, this happens a few weeks before the record date. The company specifies the amount of the dividend and sets the record date and payment date. The record date is the date that one must be in the books of the company to receive a dividend. Ex-dividend date is set based on the record date and the different exchange rules. Normally, the ex-dividend date is set one or two working days before the record date. In the figure below the ex-dividend date and record date is set on Friday and Monday respectively, which makes them one working day apart. The last step in the process is the pay date, which is when the companies pay out the dividends to the shareholders. This normally happens one week or more after the record date (Investor.gov, n.d.).

For a shareholder to have the right to receive dividends they must buy shares no later than the day before the ex-dividend date. This is referred to as the cum-date. Simultaneously, if a shareholder sells their shares before the ex-dividend date, they lose the right to receive dividends. In the figure below, anyone who bought the shares before 15.09.17 will receive dividends. Conversely, the ones who sold their shares before this date will not receive dividends.

The cum-schemes presented in section 2.7 involves transactions around the ex-dividend day. The common denominator is that the ADRs are lent out no later than the day before the ex-dividend date such that the dividend is included.

Figure 2: Example of distribution process

Declaration Date	Ex-Dividend Date	Record Date	Payable Date
Friday, 9/8/2017	Friday, 9/15/2017	Monday, 9/18/2017	Tuesday, 10/3/2017

Source: (Investor.gov, n.d.)

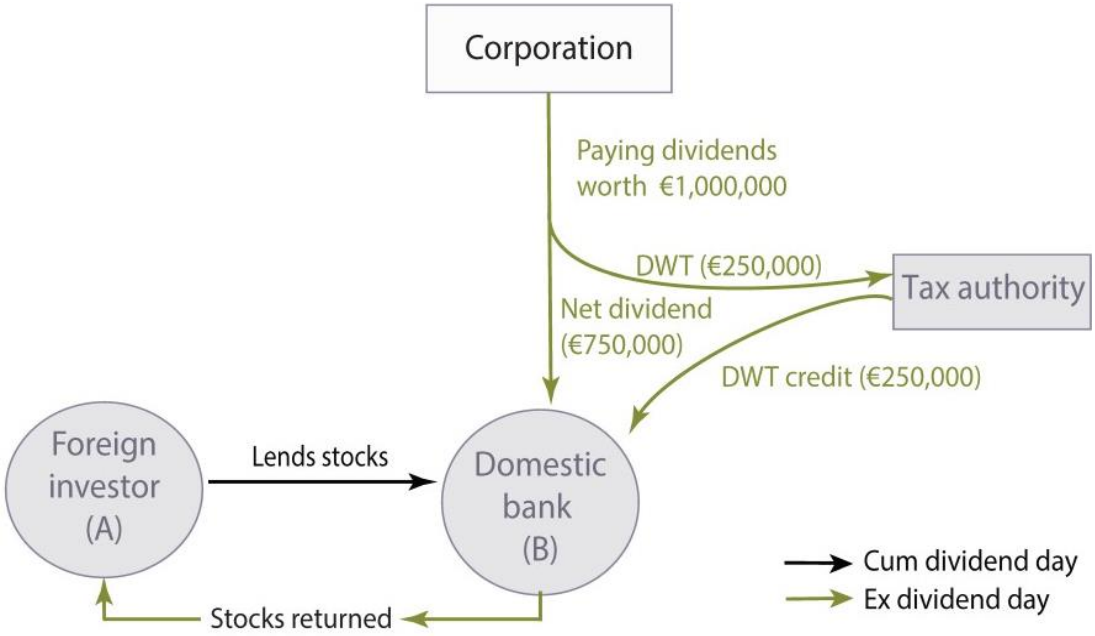
2.7 Cum-Cum, Cum-Ex and Cum-Fake Transaction

There are several cum-schemes that involves trading across borderlines around the ex-dividend date. We provide an explanation of the most common schemes to provide a better basis for our thesis.

2.7.1 Cum-Cum Transaction

The cum-cum scheme implies that securities are lent to an across border party that have access to better withholding tax reclaims than the original owner of shares. Figure 3 presents a typical example of a cum-cum transaction. The original owner of shares lends stocks cum-dividend to a domestic party, often a financial intermediary, with an agreement that the shares are bought back later. The domestic party is often exempt from dividend-withholding tax. After the record date, the dividend withholding tax is deducted, and the domestic party receives the net dividend. They transfer it back to the original owner with a security lending fee as compensation. Since this fee is not considered as income, it is exempt from taxes and considered tax-free. Because the domestic investor generally is exempt from the dividend-withholding tax, they are eligible to receive a full refund. This scheme enables the original owner of the shares to circumvent the dividend-withholding tax (Casi et al., 2022).

Figure 3: Cum-cum scheme



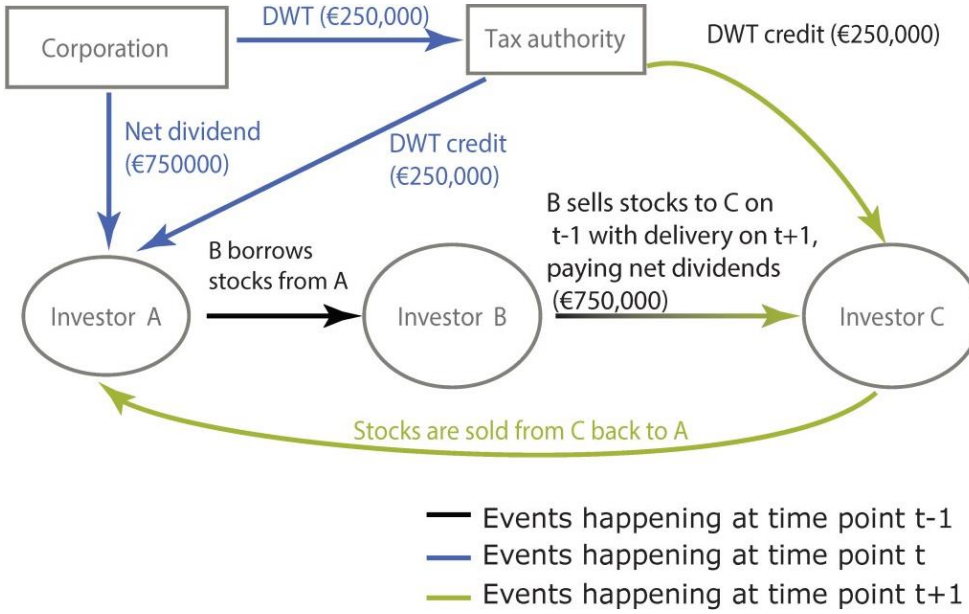
Source: (Casi et al., 2022)

2.7.2 Cum-Ex Transaction

While the cum-cum scheme seeks to evade the dividend withholding tax, a cum-ex transaction aims to obtain multiple tax refunds on a tax that has only been paid once. This is achieved by rapid buying and selling of shares between multiple parties around the ex-dividend date. The aim of this tactic is to obscure the identity of the legal owner of the shares, thereby making it challenging for tax authorities to determine who is entitled to claim a tax refund.

Figure 4 presents a typical cum-ex transaction, executed by three investors. Before the ex-dividend date, investor A lends shares with attached dividends to investor B. Without yet owning the shares, Investor B immediately sells them to Investor C and pays an additional amount corresponding to the net dividend payment. This is possible because there is a latency between the conclusion of the transaction and the delivery of the shares. For the same reason the shares that are sold to investor C are delivered after the dividend payment date. At the dividend payment date, the corporation pays net dividends to Investor A and withholds the required percentage of tax and transfers them to the tax authorities. They also receive a tax certificate to reimburse dividend withholding tax. The following day, Investor C also receive a tax reimbursement certificate and sells the shares back to Investor A. The tax reimbursements are shared between the three investors (RahmanRavelli, n.d.).

Figure 4: Cum-ex scheme



Source: (Casi et al., 2022)

2.7.3 Cum-Fake Transaction

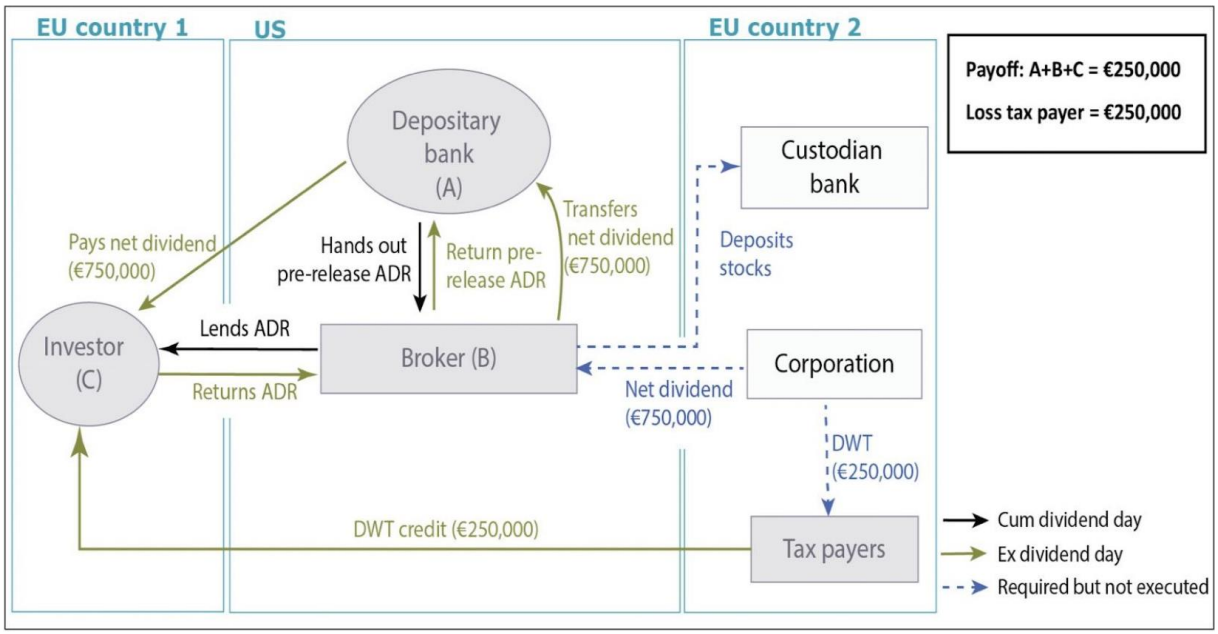
In the cum-fake transaction, the tax refund is claimed on a withholding tax that was never paid. This is typically accomplished by brokers who intentionally fail to comply with the requirement to deposit shares in a custodian bank and depositary banks neglecting to ensure that brokers are fulfilling their pre-release agreements (Securities and Exchange Commission, 2018d; Securities and Exchange Commission, 2017c).

Figure 5 presents an example of a cum-fake scheme. The parties involved are a depositary bank and a broker in the U.S., and an investor in a foreign country. At the cum-dividend date the depositary bank issues a pre-released ADR to the broker which immediately lends it to the investor in the foreign country. The action is carried out without the broker acquiring the underlying shares. This creates a misleading impression that the broker has obtained them.

On the ex-dividend date, the broker pays an artificial dividend payment to the depositary, who in turn pays this amount to the foreign investor. After receiving the artificial dividend, the foreign investor returns the pre-released ADRs to the broker, who in turn returns them to the depositary. This results in the position being closed by returning the pre-released ADRs to the depositary, rather than delivering the underlying shares to the custodian as originally intended.

After the position is closed the foreign investor applies for a tax credit. The tax credit corresponds to the amount of dividend withholding tax that the tax authorities believe has been paid. In the following example, it is 25% of $ 1 000 000, i.e., $ 250 000. This is a direct loss for the taxpayers since no tax has been paid. The tax credit is split between the three parties.

Figure 5: Cum-fake scheme



Source: Floris T. Zoutman

2.7.4 Mechanism of a Fraudulent Pre-Release Transaction According to the SEC

Table 4 present a fraudulent pre-release transaction (cum-fake) as described in the orders by the SEC. The table applies a tax of 30 percent.

The dividend from the public company is collected by a tax-exempt counterpart. No tax is paid. The result of this is that the tax-exempt party now has a net dividend of 100%. The tax-exempt party forwards the originally intended net-dividend of 70% as well as 20% of the tax savings to the pre-release broker in the U.S., thus retaining 10% for himself. The pre-release broker then forwards the net dividend of 70% as well as 10% of the tax savings to the custodian bank, retaining 10% himself. Lastly, the custodian bank forwards the net dividend of 70% to the and retains the final 10% of the tax savings. This leaves the ADR investors with

a net dividend of 70%. The 30% that is divided among the three parties is allocated through lending fees (Lenz, 2019).

In an ordinary ADR transaction, the dividend would not have been paid directly to the tax-exempt party. Rather, the dividend would have been delivered to the sub-custodian of the U.S. custodian in the foreign country, with the tax being withheld there. The objective with a fraudulent pre-release transaction can thus be seen as a means to manipulate the dividend-payment stream such that the tax burden disappears (Lenz, 2019).

Table 4: Mechanism of a fraudulent pre-release transaction

Steps	Countries	Actors	Actions
1	Foreign country	Joint-stock companies	Pays gross dividend (100%)
2		Central Securities Depository Equities (Clearstream)	Forward them
3		Sub-custodian (custodian bank) of the tax-exempt counterpart	Does not pay capital gains tax, pays gross dividend (100%)
4	Country with a claim for reimbursement	Depositary bank of the tax-exempt counterpart	Forward them
5		Tax-exempt counterpart	Passes on net dividend (70%) + tax savings (20%), retains 10%
6	United States	Pre-release broker	Passes on net dividend (70%) + tax savings (10%), retains 10%
7		Custodian	Passes on net dividend (70%), retains tax savings (10%)
8		ADR Central Securities Depository (Central Securities Depositori) (Central Securities Depository)	Passes on net dividend (70%)
9		ADR Investors	Receives net dividend

Source: Own contribution, inspired by (Lenz, 2019)

The schemes described above and in section 2.7.3 seem to be a variant of the cum-cum scheme. In both cases, the aim is to dodge the withholding tax by lending the ADRs to an overseas entity that has a tax-advantage. There is no indication of multiple tax refunds, a characteristic associated with a cum-ex transaction.

3 Research

The beginning of this chapter introduces our research question as well as the hypothesis and objective we formulated to help us tackle it. We then look at the data collection process and its challenges. Finally, we go through our analytical framework and explain the choices we have made regarding the regression models and methods we use.

3.1 Research Question

The aim of this thesis is to investigate in which European countries ADRs have been used as a part of cum-fake trading, and if we can identify when it has been used most prevalently. We are examining the daily trading volume for all European ADRs and are doing a country-by-country analysis on whether there is abnormal trade volume on or around the ex-dividend date. Previous literature suggests that a significant spike in trading volume on or around the ex-dividend date is connected with cum-ex trading. We do not create further evidence for this. Instead, we assume that spikes in ADR trading volume is connected with cum-fake trading. This is the baseline into our investigation of where and when cum-fake trading has happened.

To accomplish this objective, we have one hypothesis we test for and one objective we investigate by exploring our data:

Hypothesis: Some European countries have significantly higher trading volume on and around the ex-dividend date.

The hypothesis is based on the fact that a country's laws and systems must be exploitable by the cum-fake scheme for it to have a payoff. Therefore, we expect to see differences in the trade volume on and around the ex-dividend date between countries.

Exploratory objective: Is it possible to find certain time periods that shows clear signs of cum-fake trading in each country?

This objective refers to how the environment for cum-ex trading has changed throughout the years in different countries. We expect to find when the markets were at their most exploitable. This could also possibly show when measures were taken to combat the cum-fake trading in each country.

3.2 Data Collection

Our analysis aims to look at all European companies that have issued ADRs. We retrieved a list of these companies from JPMorgan's depository receipt directory, filtered to include both Eastern and Western Europe (including Russia and Turkey). The daily trading volume, dividend dates and country of origin for these companies were then gathered from the Compustat database. Our timeline goes back as far as possible, which in Compustat means 1984. However, we soon realised that a lot of the trading volumes in the data were set to 0. A possible reason is that most ADRs are traded over the counter instead of on an exchange, and therefore does not show up in the database. Comparing samples with other databases like Yahoo, Bloomberg and Eikon's Refinitiv, we saw that the trading volumes of 0 must be wrong but that the dividends and dividend dates were aligned between the databases.

Our solution is to get the trading volumes from Refinitiv and merge them with the dividend dates from Compustat. The issue with this development is that Refinitiv only goes back 20 years. For some companies that should have older data, the data now starts at the 15th of February 2003. This goes against our initial wish of looking at the full timeline for all companies. However, given the circumstances we believe this is the best possible alternative. As for the companies that Compustat gave actual trade volume for (these numbers were also checked in samples towards the other databases, and they seemed to concur), we chose to keep the Compustat values. This means there are still companies with data going further back than 2003, but not as many as there should be. We realise this might affect our results, and it is taken into consideration.

Since the analysis is done on a country-by-country basis, we divide the companies into country-specific datasets. We make the ex-dividend date into a binary variable, as well as different binary variables for 3 days on either side of the ex-dividend date. We choose this approach of seven one-day periods over creating one seven-day period to help us see if countries have similar or different patterns. We transform the trading volumes into their natural logarithmic values.

For the exploratory analysis, we no longer use the natural logarithmic values. Instead, we take out the fixed effects manually by calculating the yearly average trading volume for each

company. We then use the average yearly trading volume to calculate the daily deviation from the average in percent using this formula:

$$AV_{itk} = \frac{(TV_{it} - ATV_{ik})}{ATV_{ik}} * 100$$

AV is the abnormal volume or deviation variable for company (i) in time (t) in year (k). *TV* is the daily trading volume for company (i)in time (t). *ATV* is the average trade volume for each company (i) in year (k).

We filter the datasets to only include the ex-dividend date and the two days on either side. Hereby creating one five-day period instead of the seven one-day periods in the first analysis. This choice is made as the specific daily volume is more relevant to the first hypothesis. Once that is known we use one longer period to easier find usable results for our second objective.

3.3 Descriptive Statistics

The data collection process generates 1.123.366 observations of daily trading volume, spread over 328 different companies who again were divided into 20 countries. Of all the daily observations, 6435 of them were ex-dividend dates. Table 5 shows the distribution of companies, total observations and ex-dividend dates for each country.

Table 5: Descriptive statistics for each country

Country	Companies with ADRs	Total Observations	Ex-Dividend Dates
Austria	7	15,447	64
Belgium	8	18,524	95
Denmark	12	36,886	160
Finland	10	30,791	134
France	46	166,839	760
Germany	42	123,989	447
Greece	2	7,452	18
Hungary	2	6,980	23
Ireland	10	42,501	208
Italy	12	37,845	168
Luxembourg	4	15,967	75
Netherlands	16	51,987	300
Norway	9	33,840	194
Portugal	3	9,834	52
Russia	8	27,167	136
Spain	20	73,511	641
Sweden	20	65,140	294
Switzerland	21	66,061	274
Turkey	5	13,624	50
United Kingdom	71	278,981	2342

3.4 Framework

The analysis is done in two parts to answer the different aspects of the research question. The first part is an event study with panel data of all European companies that have ADRs. We run a fixed-effects regression with binary variables and clustering of standard errors on 20 different datasets, one for each country. The aim is to find which countries have experienced significant spikes in trading volume around the ex-dividend date in a 95% confidence interval.

Mathematical formula for the first regression model:

$$LogVolume_{itk} = \beta 1B3_{it} + \beta 2B2_{it} + \beta 3B1_{it} + \beta 4D_{it} + \beta 5A1_{it} + \beta 6A2_{it} + \beta 7A3_{it} + \alpha_{ik} + \varepsilon_{it}$$

LogVolume is the natural logarithm of the trading volume for company (i) at time (t) in year (k). Using the natural logarithm instead of the raw trading volume smooths out what could be huge differences in company attributes like size and volatility. (*D*) is a binary variable equal to 1 on the ex-dividend date for company (i) in time (t) and 0 otherwise. *B3-1* and *A1-3* are binary variables indicating when the observation was made in regard to the ex-dividend date. It spans the period of *B*3 being 3 days before the ex-dividend date, until *A*3 which is 3 days after. α is the fixed effect for company (i) in year (k), and (ε) is the error term for the observation for company (i) at time (t).

An additional reason for using LogVolume is that we can use it to show the relationship between the estimated volume on and around the ex-dividend date and the estimated volume on any given day as a percentage. To calculate the correct percentage from the LogVolume, we have used the method described by Kennedy (1981) as a starting point.

$$p = \left(\exp\left(LogVol - \frac{1}{2}V(LogVol)\right) - 1\right) * 100$$

Where (p) is the difference between the general estimation and the estimation of one of our selected days. *LogVol* is the estimated LogVolume, and *V(LogVol)* is the variance of the estimated LogVolume. In a setting like this, including the variance when transforming the logarithmic values into percentages gives a less biased result than the more generally used formula (Kennedy, 1981).

In our case that formula would look like this:

$$p = (\exp(LogVol) - 1) * 100$$

For the second part of the analysis, we continue with the countries that show positive signs of cum-fake trading. Since the datasets now only contain days surrounding the ex-dividend dates, we run a linear regression where we regress the abnormal volume or deviation variable on the year. The aim is to find the years in each country where the dividend period trading volume is significantly higher than the yearly average in a 95% confidence interval.

Mathematical formula for the second regression model:

$$AV_{it} = \beta 0 + \beta 1 Y_{it} + \varepsilon_{it}$$

Where *AV* is the Abnormal Volume or Deviation variable for company (i) at time (t). (Y) is the Year, and (ε) is the error term.

3.5 Fixed Effects and Clustering of Standard Errors

The companies analysed in our regression model may differ from each other in ways that are not directly measurable or observable. The unobserved factors can affect the dependent variable and further lead to the estimates of the regression coefficients being biased. Fixed effects are used to control for this unobservable heterogeneity. We fixed our models on the interaction between company and year, meaning that each unique combination of company and year is given a separate fixed effect. The inclusion of the time fixed effects is done because we believe there are unobservable differences in the ADR market and usage for each company over time, and not just between the companies.

There is a possibility that there are correlations within the observations. While the fixed effects control for parts of the within-cluster correlation of the error, it generally does not control for it completely. Due to the differences in size between our datasets, we use two methods of clustering. For countries with 20 or more companies, we use cluster-robust standard errors (Cameron & Miller, 2015). Cluster-robust standard errors is a form of two-way clustering that adjust the regression results to account for these within-cluster correlations. We have identified Company and Year as the areas where our data might have correlations. This is

because the data could have been affected by both company and year specific information that is unrelated to cum-fake trading. Thus, creating a correlation between the data in certain areas that we wish to adjust for.

For the countries with less than 20 companies, we use cluster bootstrapping on the standard errors. There are different methods of cluster bootstrapping. Cameron, Gelbach and Miller (2007) find that for models with few clusters, the wild cluster bootstrap is efficient. Therefore, we use the wild cluster bootstrap, also called the Webb method, for our datasets with 3-19 clusters. We choose the recommended number of bootstraps B = 999 (Cameron, Gelbach, & Miller, 2008). As this method uses one-way clustering, we chose Company as the clustered variable for the same reasons as mentioned above. The reason we went with Company over Year is that we assume it would be more likely to exist correlations based on company. Since it is impossible to bootstrap clustered standard errors with only two clusters, Greece and Hungary use the cluster-robust standard errors. The results are most likely biased, and that is taken into consideration.

The layout of the results differs between the two methods. For the countries using cluster-robust standard errors, there has been only one regression per country and the summaries are in the appendix. For the smaller countries, the seven days (B3-A3) had to be bootstrapped individually and then later put together. Therefore, we choose to include the regression results from both before and after the bootstrapping of the clustered standard errors in the appendix. This is done to give a better picture of the summary statistics. For the analysis we use the estimates and significance levels given after the bootstrap.

4 Empirical Analysis

In this chapter we present the results of our analysis. We start by looking at the results from the regressions on the ex-dividend date trading volume, done country-by-country on the full datasets. Afterwards, we present the results from the exploratory analysis on the yearly data for the countries that show positive signs of cum-fake in the first part of the analysis. We look at both the statistically significant years for each country and take a closer look at each country graphically.

4.1 Daily Trading Volumes on and Around the Ex-Dividend Date

Our main research question is to see if we can find evidence to suggest which countries have experienced cum-fake trading. As previously explained in the theoretical part of the thesis, a significant rise in trading volume of ADRs on and closely around the ex-dividend date suggests that cum-fake trading has occurred. The results of our analysis show that the countries can be divided into three categories:

- Countries with a significant spike in trading volume on the ex-dividend date and on some surrounding days.
- Countries with a significant spike in trading volume on one or more days surrounding the ex-dividend date but not on the main day itself.
- Countries with no significant relationship between trading volume and the ex-dividend date or any of the surrounding days.

The group of countries with a significant result on the ex-dividend date is shown alphabetically in table 6. The table only includes the results for the ex-dividend date. The column labelled “Abnormal Volume” shows the relationship between the estimated trade volume on that given day and the overall estimated trading volume in percent.

Table 6: Countries with significant increases on the ex-dividend date

Country	LogVolume	Abnormal Volume
Austria	0.709	99.47%
Belgium	0.300	33.99%
France	0.156	16.66%
Spain	0.240	26.77%
Sweden	0.114	11.87%
United Kingdom	0.137	14.61%

Of the six countries in this group, Austria clearly has the highest increase in trading volume on the ex-dividend date. Belgium and Spain also show a clear spike. France, Sweden and the UK all gave significant results, but with lower spikes.

For Austria and Belgium, the ex-dividend date was the only day in the seven-day dividend period that gave significant results. UK on the other hand, gave significant results for all days in the span of Before2-After2 (where Before2 is 2 days before the ex-dividend date, and so on), as seen in table 7. The fact that UK is significant at all could initially be seen as surprising since the UK does not currently levy a withholding tax on dividends, hence, cum-fake trading should be pointless. However, our UK data goes back to 1985 and they did not abolish the withholding tax until 2008 (Casi, Gavrilova, Murphy, & Zoutman, 2022).

Like the UK, Spain also has significant results for all days in a five-day period. The period spans from Before1-After3. Unlike the UK, the ex-dividend date clearly has the largest spike. This also means that the Spanish abnormal volume has a much larger range, spanning from 12.04% to 26.77%, compared to the UK with 9.33 to 14.83%.

France also gives significant results for the days after the ex-dividend date, but with increases much closer to the one on the ex-dividend date. As for Sweden, the day after the ex-dividend date is significant. What differentiates Sweden is that the day after clearly has a larger spike than the ex-dividend date. Sweden's estimated abnormal trading volume on the ex-dividend date is 11.87%, while the day after is up to 20.82%. Table 7 presents the results for the other significant days for the countries in the first group.

As presented in Figure 6, out of the four countries, Spain is the only one where the ex-dividend date has the largest estimated abnormal value. This is surprising as we expected the trading volume on the ex-dividend date to be the clearest estimator of cum-fake trading due to the nature of the scheme.

Figure 6: Abnormal volume for the significant days of selected countries

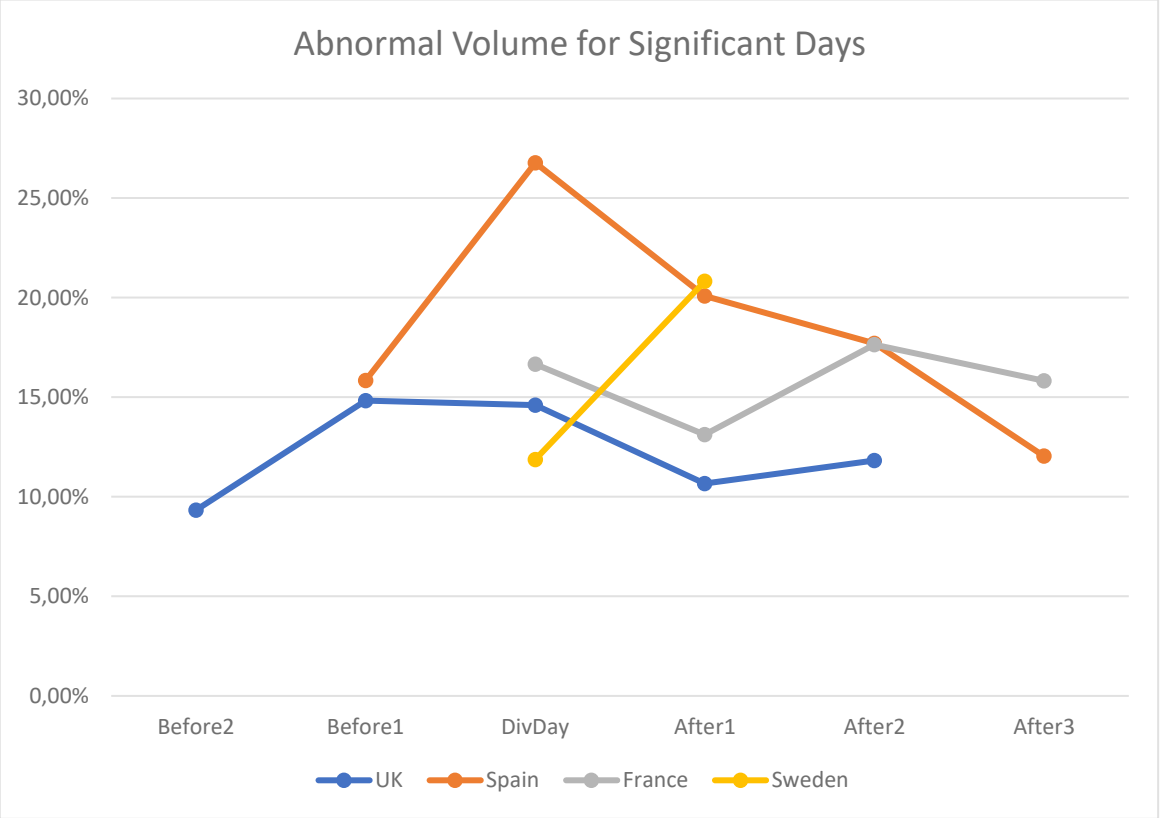


Table 7: Significant surrounding days for countries with significant ex-dividend dates

Country	Day	LogVolume	Abnormal Volume
France	After1	0.124	13.12%
France	After2	0.163	17.64%
France	After3	0.148	15.82%
Spain	Before1	0.148	15.84%
Spain	After1	0.186	20.09%
Spain	After2	0.166	17.71%
Spain	After3	0.115	12.04%
Sweden	After1	0.193	20.82%
United Kingdom	Before2	0.089	9.33%
United Kingdom	Before1	0.139	14.83%
United Kingdom	After1	0.102	10.67%
United Kingdom	After2	0.112	11.82%

The second group of countries are the ones with significant estimated abnormal volume on one or more days that does not include the ex-dividend date. The countries are Denmark, Finland, Greece, Luxembourg and Switzerland. Table 8 presents which days relative to the ex-dividend date that are significant and the corresponding estimated abnormal volume.

Table 8: Countries with significant increases on days around the ex-dividend date

Country	Day	LogVolume	Abnormal Volume
Denmark	After1	0.162	17.27%
Finland	Before1	0.368	43.85%
Finland	After3	0.266	29.97%
Greece	Before1	-0.447	-36.07%
Luxembourg	Before3	0.185	19.86%
Switzerland	After1	0.144	15.24%

Finland is the only country in this group to have two significant days. Both days have a higher estimated abnormal volume than the rest of the countries. Denmark and Switzerland both have the day after the ex-dividend date as their significant day, and with similar values.

The only significant day for Luxembourg is three days before the ex-dividend date. Considering the fact that Luxembourg has one of the smallest datasets with only four companies, we theorize that there is a possibility this result could be explained by reasons other than cum-fake trading. Greece is the only country with a significant negative estimated abnormal volume. The estimated trading volume is 36.07% lower than normal on the day before the ex-dividend date. We have earlier pointed out that we find it hard to trust the Greek and Hungarian results due to the small datasets and lack of bootstrapping for the clustered standard errors. For these reasons we decide to continue without Luxembourg and Greece in the exploratory part of the analysis even though they technically fulfil the requirements.

The final group of countries were those that had no significant increases on the ex-dividend date or any of the surrounding days. The countries included in this group are Germany, Hungary, Ireland, Italy, Netherlands, Norway, Portugal, Russia and Turkey. With Germany at the heart of the cum-ex scandal that has been uncovered in recent years, we are surprised to see them in this group. However, this has to be explored further and we continue our analysis with the results we get. It could be worth noting that if we had chosen a confidence interval of 90% instead of 95%, this group would only consist of Germany, Hungary and Turkey. Regardless, the exploratory part of our analysis excludes all the countries in this group as well as Luxembourg and Greece as explained earlier.

4.2 Yearly Abnormal Trading Volume per Country

In the second part of the analysis, we explore the data to see if we can identify certain years that have seen a significant amount of cum-fake trading in each country. We first look at the significant years from the regression models, then go through all the estimates country by country.

Table 9 provides an overview of all significant years for each country as well as the estimated abnormal volume in percent for the five-day period surrounding the ex-dividend date. It is worth noting that Belgium and Finland do not have any significant years. In the case of Finland, they might be affected by our decision to not include After3 in this part of the

analysis. However, their Before1 does have the second largest estimated abnormal volume behind Austria's ex-dividend date.

Austria, Denmark and France each have only one significant year with a very high estimated abnormal volume. Denmark in 1996 show the highest deviation from the yearly average in the dividend period with an estimated increase of 1388.49%. Spain, Sweden and UK have a group of significant years in the middle of the 1990s. Switzerland has three significant years, but in three different time periods. Switzerland also has a lower deviation from the yearly average than the other countries, with UK 1993 being the only other significant year with a similarly low value.

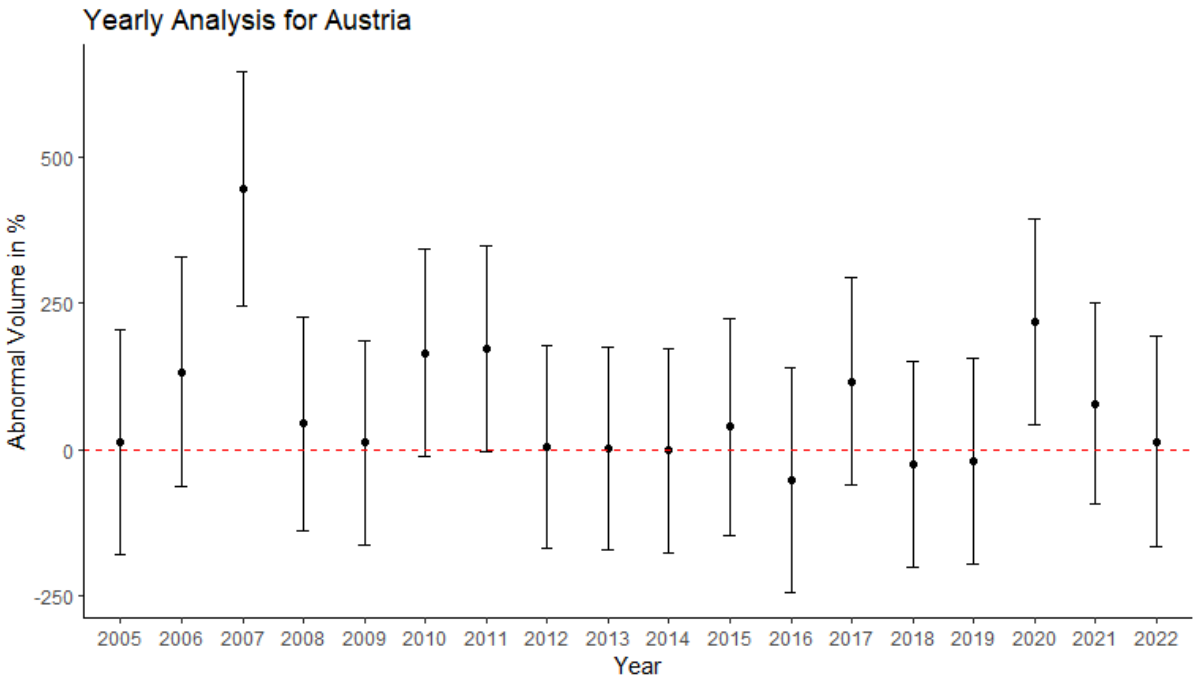
Table 9: Years with significant increases per country

Country	**Year**	**Abnormal Volume**
Austria	2007	446.50%
Denmark	1996	1388.49%
France	1993	855.82%
Spain	1994	327.60%
Spain	1995	441.84%
Spain	1996	561.80%
Spain	1997	388.66%
Sweden	1994	393.99%
Sweden	1996	470.54%
Sweden	1997	465.69%
Switzerland	1997	255.93%
Switzerland	2009	155.18%
Switzerland	2018	138.28%
United Kingdom	1993	179.60%
United Kingdom	1994	339.67%
United Kingdom	1995	271.98%
United Kingdom	1996	763.33%
United Kingdom	1997	341.42%

The following graphs (figure 7-15) illustrates the estimates from each country's regression on yearly abnormal trading volume for the five-day period around the ex-dividend date. The red line is the yearly average for each company where the abnormal volume or deviation is 0%. The estimated trading volume for the dividend period in relation to the yearly average is then shown by year. The dot represents the estimated abnormal volume, while the lines are the standard errors for each estimate. We comment on each of the figures as they are presented.

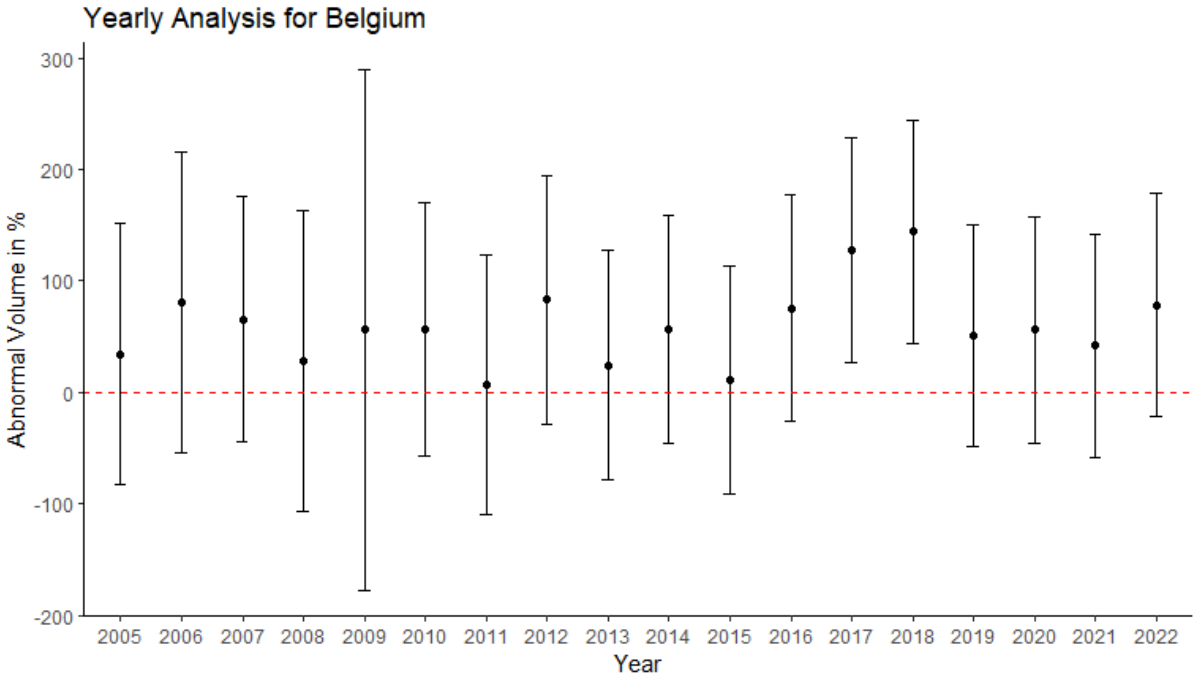
The result from Austria shows that the significant year is also the one with the highest estimated abnormal volume. The data begins in 2005 with trading volume close to the yearly average. Then come the years 2006, 2010 and 2011 with high values, although not close to the spike of 2007. Since then, there have been sporadic years with higher abnormal volume, especially 2020.

Figure 7: Yearly analysis for Austria



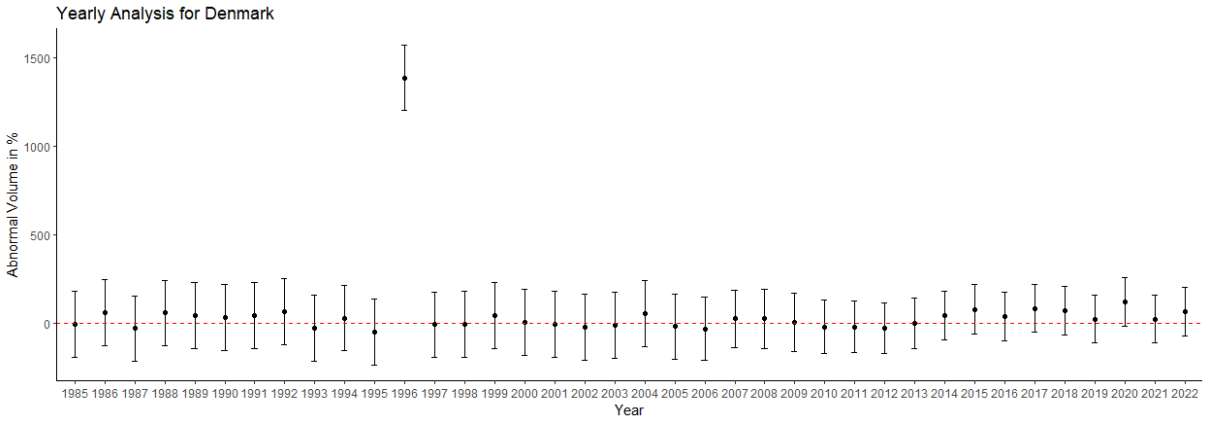
Belgium does not have any significant years. It is still interesting to see how the estimates suggest that the trading volume in the dividend period is between 50%-100% larger than the yearly average for most years. In 2017 and 2018, it even surpasses the 100%-mark. 2009 also stands out with a much larger standard error than the other years.

Figure 8: Yearly analysis for Belgium



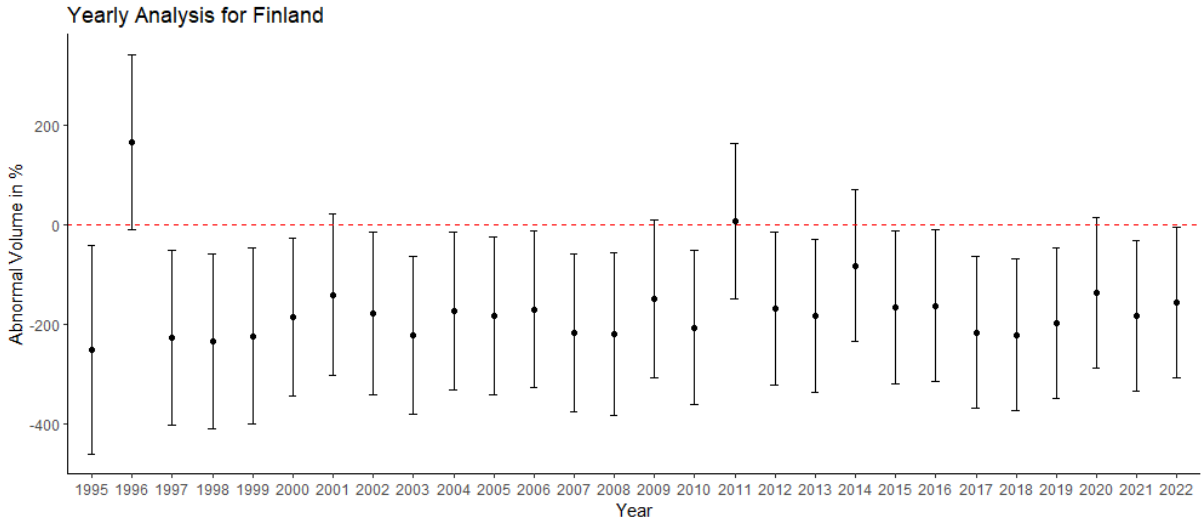
Denmark's timeframe is longer compared to the previous two countries as it goes all the way back to 1985. Due to the massive outlier in 1996 that reaches over 1300%, it is hard to extract nuanced information from this graph. It is clear that the abnormal volume has been notably higher since 2014, compared with the results from the late 1990s and 2000s.

Figure 9: Yearly analysis for Denmark



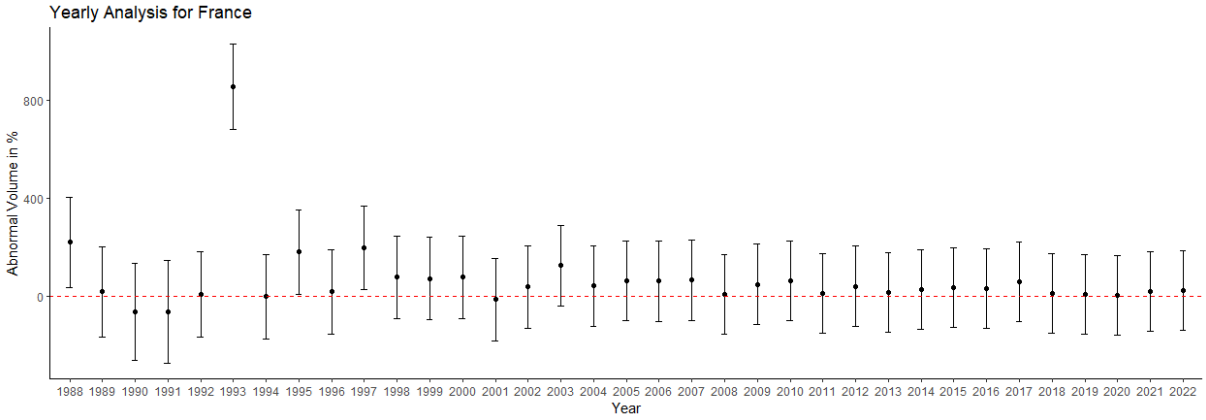
Finland is the other country that has no significant years. The results here are really puzzling, as only two years show an estimated trading volume in the dividend period that is higher than the yearly average. Table 17 shows that none of the days included in this part of the analysis gave negative estimations in the overall regression, so this is surprising. This needs further examination.

Figure 10: Yearly analysis for Finland



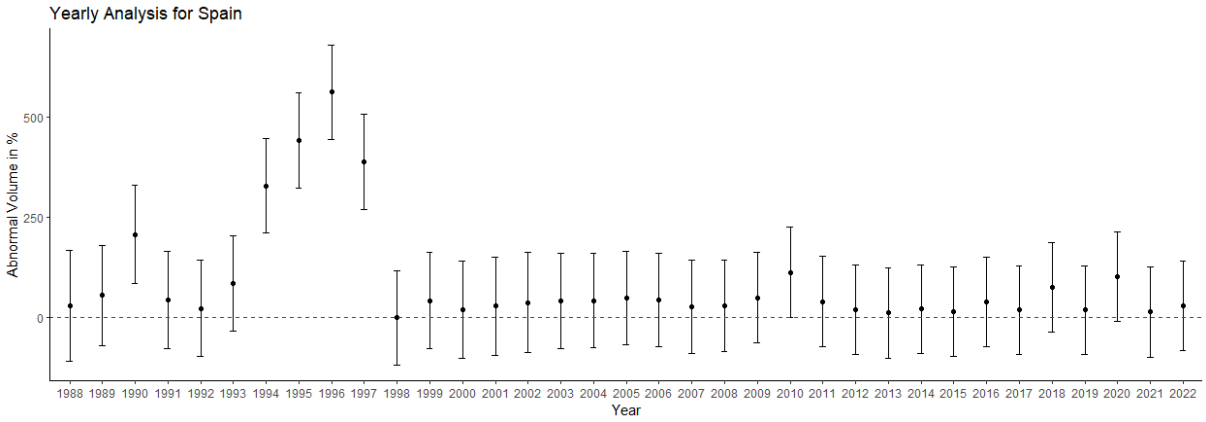
France, like Denmark and Austria, have one significant year. Similar to the other two, the significant year is the clear outlier. In the case of France, that year is 1993 with 855.82%. In the following years, 1995 and 1997 almost reach 200%. The years after this have relatively high estimates up towards 100%, with a dip in 2001. After a spike in 2003 with 125.46%, we can see a steady decline towards today.

Figure 11: Yearly analysis for France



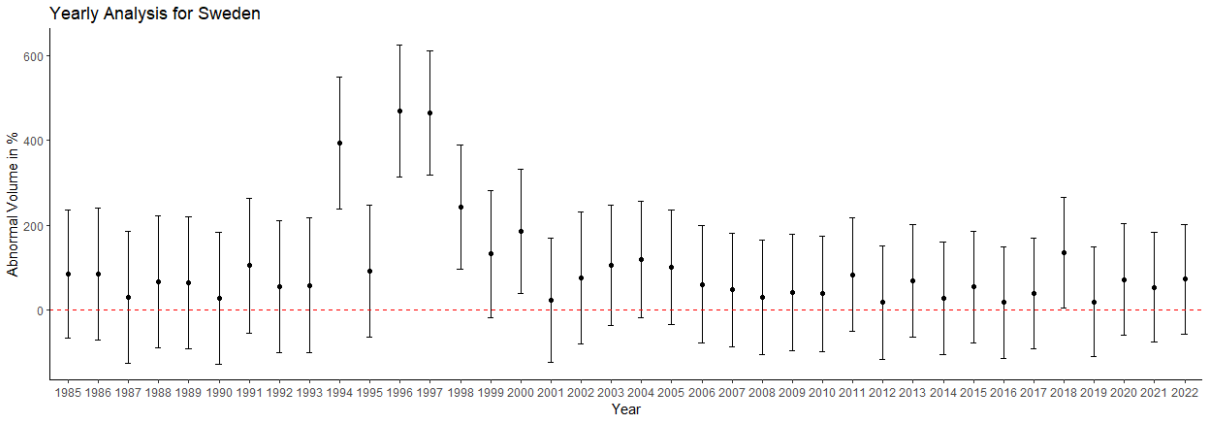
Spain shows clear signs of cum-fake trading in the mid-1990s, with a significant four-year period between 1994-1997. The estimates for the available years before this period are relatively high as well. In 1990, the estimated trading volume reaches 206,71%. Since then, the estimated trading volume for the dividend period have been around 40% higher than the yearly average. However, it did go above 100% in both 2010 and 2020.

Figure 12: Yearly analysis for Spain



Sweden, like Spain, shows clear signs of cum-fake trading in the mid-1990s. The significant period is almost the same. The main difference is 1995, which for Sweden is both not significant and more on the level with the years outside 1994-1997. Both before and after this period, the estimates seem to fluctuate almost in a wave-pattern. The estimates are generally quite high. 1998-2000, 2003-2005 and 2018 all reach above 100%.

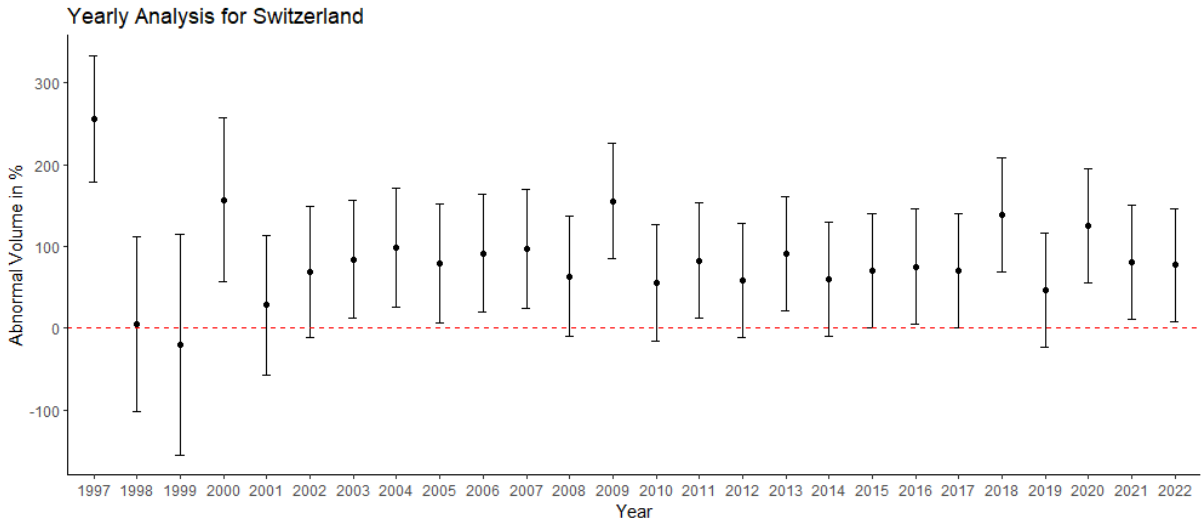
Figure 13: Yearly analysis for Sweden



Switzerland distinguishes themselves with their significant years, as they are the only country to have multiple significant years in completely different periods. As illustrated in the graph,

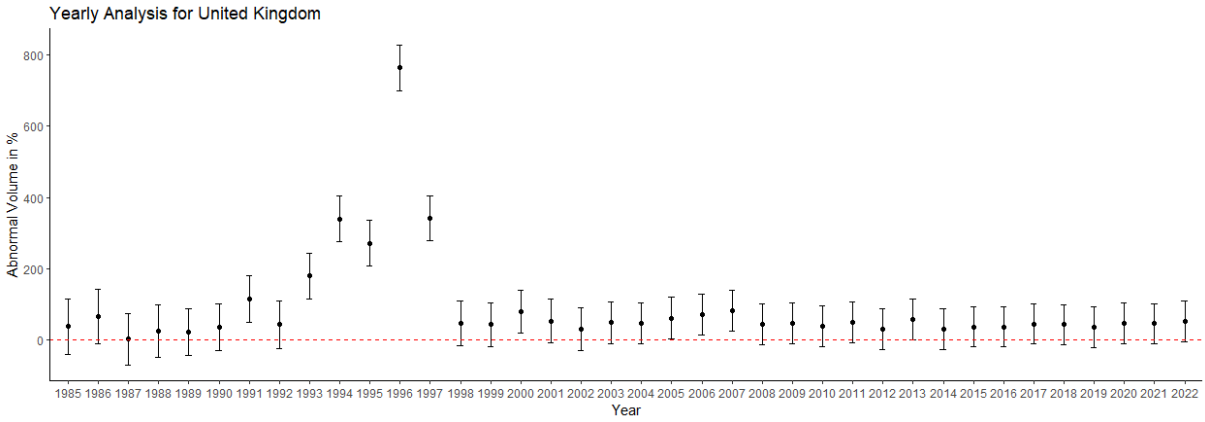
the significant years of 1997, 2009 and 2018 have higher estimates than usual. However, the same applies for 2000 and 2020, which are not significant. It is interesting that while the significant years have a lower estimate than significant years for other countries, many of the other years have quite high estimates in the range of 70%-100%.

Figure 14: Yearly analysis for Switzerland



The UK shares similarities with Spain and Sweden. Their significant period is 1993-1997, with the highest estimate in 1996. Since then, the estimates are mostly hovering around 40%. It could also be worth noting that UK has the smallest standard errors of the countries analysed in this part.

Figure 15: Yearly analysis for United Kingdom



Comparing the results from each country, we can see certain patterns emerging. The time period of 1993-1997 is recurring as a period where the trading volume in the five-day

dividend period was substantially higher than the yearly average. 1996 stands out with the highest estimated trading volume for five of six countries with data from this year. The years 2018 and 2020 also sees higher estimates than the years around them in several countries. Although rarely both years for the same country. Overall, except for Finland and Denmark, most estimates are consistently positive in relation to the yearly average.

Since most of the previous literature in this field is exploring timelines somewhere between 2000 and 2020, we assumed our significant findings would also be from this period. Instead, that period shows little to nothing in terms of consistent spikes in trading volume compared to the yearly average. One explanation could be that cum-fake trading is a smaller phenomenon than we anticipated and does not impact the trading volume to a large enough extent. There is a possibility that examining the ADR trading volume, as done by Spengel (2021a) and us, may not be the most effective method for detecting cum-fake trading.

To our knowledge, there is no specific research on the extent of cum-ex and cum-fake trading in the 1990s. However, there are reports of the first cases of cum-ex trading in Germany as early as 1992 (Wagner & Wei, 2020). This means that there is a possibility that cum-fake trading was more frequent in the 1990s. However, it is important to acknowledge that the data from this period is not as strong as the more recent years. This is both due to fewer companies issuing ADRs at that time and the complications with our data retrieval.

We are also left with certain curious findings from this exploratory part of the analysis that we find hard to explain. First and foremost is Finland with their mostly negative estimates. Not only are they the only country where this is observed, but the negative estimates are also very strong, ranging usually between -150% to -230%. There are also the cases with the countries that have one year that is a massive outlier, like Denmark, Finland and France. Lastly, we have Switzerland. They differentiate themselves by having several spikes, but in wholly different time periods. Both the patterns and the anomalies we have found need further research.

4.3 Limitations

Our main analysis suggests that cum-fake trading has happened in six European countries, with the possibility of four more. While the results show that there is a significant relationship between trading volume and the days surrounding the dividend day, the estimated spikes are

lower than expected with the exception of Austria. This could be a consequence of the unusually large timeframe we have chosen.

With our approach to look at the days surrounding the dividend day individually, there are also the cases of the countries with significant days other than the dividend day. While the results for ex-dividend date are the most important given the nature of the cum-fake scheme, we choose to include three of these countries based on previous findings that the trading volume peaks can come around the dividend days as well (Spengel, 2021a)

Another limitation is the sizes of some of the datasets. 9 of the 20 countries have less than ten companies to work with. While the results can still be meaningful, there is a chance that outside disruption can impact the overall results of the analysis. There are also differences in how long each company has issued ADRs, leading to a larger sample size the closer we get to today.

The final limitation is due to troubles in the availability of data. The sample size for trading volumes earlier than 2003 are smaller than they preferably should be. The results for the earlier years could therefore be dependent on a limited number of companies, increasing the chance of outside interference. This could potentially affect the second part of the analysis which gives several significant results from the 1990s.

5 Conclusion

This thesis investigates the usage of European American Depositary Receipts in cum-fake trading. In addition, we explore which years cum-fake transactions have been most prominent in each country. Cum-fake trading is a tax arbitration scheme, utilizing loopholes in tax laws and pre-released ADRs to claim a tax refund on withholding tax that has never been paid. Our overall analysis is based on a country-by-country analysis of the daily ADR trading volume for all European companies with ADRs. Specifically seeking out abnormal surges on or around the ex-dividend date. The analysis is done in two parts. First, we find the countries that show significant signs of cum-fake trading. Secondly, we explore whether there are certain time periods that stand out with more prevalent cum-fake trading in each of the significant countries.

We have one hypothesis and one exploratory objective:

Hypothesis: Some European countries have significantly higher trading volume on and around dividend day.

Exploratory objective: Is it possible to find certain time periods that shows clear signs of cum-fake trading in each country?

For the hypothesis we achieve relatively clear results for most countries. However, the results are surprising. We know that Germany and Denmark have experienced a significant amount of cum-ex trading. For Germany to be completely insignificant and Denmark to only be significant on one surrounding day with quite low spikes is not what we expected. However, it is important to emphasise that we have not looked at cum-ex trading, but rather at trading volumes of ADRs in regard to cum-fake trading. Austria shows the clearest signs of cum-fake trading with an estimated trading volume of almost 100% higher than normal on the ex-dividend date. Belgium and Spain also show relatively high estimates on the ex-dividend date. Overall, we find signs of cum-fake trading in nine countries.

For the exploratory yearly analysis, we find certain interesting results. Belgium and Finland, who show signs of cum-fake trading in the first analysis, do not have a single statistically

significant year. Austria, Finland and France only have one significant year, and those years have unusually large estimates.

There are certain years and periods that stand out in multiple countries. The period from 1993 to 1997 encompasses the majority of spikes observed in countries with data extending that far back, with 1996 typically representing the peak. It is also worth noting that in recent years, 2018 and 2020 stand out as often having slightly higher estimates than the surrounding years. However, with much lower spikes than in the mid-1990s.

Overall, we conclude that there are differences between European countries when it comes to cum-fake trading. We theorized that the results would be clearer, but there are still significant results in several countries that suggests cum-fake trading has taken place. Our findings also suggest that cum-fake trading was perhaps not that widespread in what is considered the cum-ex era of 2000-2020. Instead, our findings suggests that it had its most prevalent period in the mid-1990s, which is an almost unexplored period within cum-fake and cum-ex research.

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Appendix

Table 10: Regression results for Austria before bootstrap

```
Austria
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                         0.121
                               (0.199)

Before2                        -0.060
                               (0.197)

Before1                         0.208
                               (0.193)

DivDay                         0.709***
                               (0.191)

After1                         -0.055
                               (0.193)

After2                         0.502***
                               (0.188)

After3                          0.092
                               (0.191)

------------------------------------------------
Observations                   15,447
R2                              0.375
Adjusted R2                     0.370
Residual Std. Error      1.523 (df = 15335)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 11: Regression results for Austria after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.121	0.514	10.64%	
Before2	-0.060	0.806	-7.63%	
Before1	0.208	0.406	20.88%	
DivDay	0.709	0.023	99.47%	**
After1	-0.055	0.788	-7.06%	
After2	0.502	0.075	62.28%	*
After3	0.092	0.745	7.70%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Regression results for Belgium before bootstrap

```
Belgium
================================================
                        Dependent variable:
                    ---------------------------
                              LogVolume
------------------------------------------------
Before3                        0.071
                              (0.122)

Before2                        0.055
                              (0.117)

Before1                        0.107
                              (0.119)

DivDay                        0.300**
                              (0.122)

After1                         0.139
                              (0.119)

After2                         0.082
                              (0.118)

After3                        -0.084
                              (0.119)

------------------------------------------------
Observations                  18,524
R2                             0.868
Adjusted R2                    0.867
Residual Std. Error     1.187 (df = 18411)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 13: Regression results for Belgium after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.071	0.598	6.52%	
Before2	0.055	0.685	4.88%	
Before1	0.107	0.327	10.46%	
DivDay	0.300	0.009	33.99%	***
After1	0.139	0.450	14.12%	
After2	0.082	0.541	7.79%	
After3	-0.084	0.598	-8.69%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Regression results for Denmark before bootstrap

Denmark

	Dependent variable:
	LogVolume
Before3	0.122
	(0.077)
Before2	0.045
	(0.076)
Before1	-0.056
	(0.076)
DivDay	0.008
	(0.076)
After1	0.162**
	(0.077)
After2	0.144*
	(0.077)
After3	0.181**
	(0.076)
Observations	36,886
R2	0.782
Adjusted R2	0.781
Residual Std. Error	0.956 (df = 36710)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 15: Regression results for Denmark after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.122	0.093	12.65%	*
Before2	0.045	0.473	4.27%	
Before1	-0.056	0.503	-5.70%	
DivDay	0.008	0.903	0.47%	
After1	0.162	0.023	17.27%	**
After2	0.144	0.109	15.19%	
After3	0.181	0.053	19.48%	*

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16: Regression results for Finland before bootstrap

Finland

	Dependent variable:
	LogVolume
Before3	-0.024
	(0.089)
Before2	0.037
	(0.090)
Before1	0.368***
	(0.090)
DivDay	0.140
	(0.089)
After1	0.175**
	(0.088)
After2	0.199**
	(0.089)
After3	0.266***
	(0.089)
Observations	30,791
R2	0.906
Adjusted R2	0.906
Residual Std. Error	1.033 (df = 30632)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 17: Regression results for Finland after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	-0.024	0.568	-2.77%	
Before2	0.037	0.591	3.40%	
Before1	0.368	0.013	43.85%	**
DivDay	0.140	0.059	14.56%	*
After1	0.175	0.201	18.62%	
After2	0.199	0.053	21.54%	*
After3	0.266	0.015	29.97%	**

Note: *p<0.1; **p<0.05; ***p<0.01

Table 18: Regression results for France

France

	Dependent variable:
	LogVolume
Before3	-0.029
	(0.040)
Before2	0.005
	(0.054)
Before1	0.032
	(0.046)
DivDay	0.156**
	(0.060)
After1	0.124**
	(0.048)
After2	0.163***
	(0.045)
After3	0.148***
	(0.041)
Observations	166,839
R2	0.810
Adjusted R2	0.809
Residual Std. Error	1.027 (df = 166094)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 19: Regression results for Germany

Germany

	Dependent variable:
	LogVolume
Before3	-0.065
	(0.058)
Before2	-0.024
	(0.066)
Before1	-0.039
	(0.052)
DivDay	0.020
	(0.052)
After1	0.115
	(0.081)
After2	0.099
	(0.093)
After3	0.113
	(0.092)
Observations	123,989
R2	0.838
Adjusted R2	0.837
Residual Std. Error	1.006 (df = 123417)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 20: Regression results for Greece

Greece

	Dependent variable:
	LogVolume
Before3	-0.219
	(0.107)
Before2	0.210*
	(0.032)
Before1	-0.447**
	(0.027)
DivDay	0.073
	(0.036)
After1	0.429
	(0.122)
After2	-0.262
	(0.129)
After3	-0.150
	(0.107)
Observations	7,452
R2	0.774
Adjusted R2	0.772
Residual Std. Error	1.261 (df = 7411)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 21: Regression results for Hungary

Hungary

	Dependent variable:
	LogVolume
Before3	-0.067
	(0.116)
Before2	0.126
	(0.433)
Before1	0.295
	(0.432)
DivDay	0.319
	(0.172)
After1	0.051
	(0.177)
After2	0.589
	(0.157)
After3	0.437
	(0.223)
Observations	6,980
R2	0.470
Adjusted R2	0.467
Residual Std. Error	1.350 (df = 6935)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 22: Regression results for Ireland before bootstrap

```
Ireland
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                         0.126**
                                (0.063)

Before2                         0.161**
                                (0.064)

Before1                          0.084
                                (0.063)

DivDay                           0.086
                                (0.064)

After1                           0.003
                                (0.064)

After2                           0.030
                                (0.065)

After3                           0.020
                                (0.064)

------------------------------------------------
Observations                    42,501
R2                               0.859
Adjusted R2                      0.858
Residual Std. Error     0.922 (df = 42298)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 23: Regression results for Ireland after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.126	0.225	13.21%	
Before2	0.161	0.080	17.21%	*
Before1	0.084	0.361	8.53%	
DivDay	0.086	0.279	8.80%	
After1	0.003	0.952	0.08%	
After2	0.030	0.750	2.86%	
After3	0.020	0.837	1.82%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 24: Regression results for Italy before bootstrap

```
Italy
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                        -0.184**
                                (0.093)

Before2                        -0.193**
                                (0.093)

Before1                         0.005
                                (0.094)

DivDay                          0.130
                                (0.094)

After1                          0.060
                                (0.093)

After2                          0.009
                                (0.092)

After3                         -0.017
                                (0.094)

------------------------------------------------
Observations                    37,845
R2                               0.727
Adjusted R2                      0.726
Residual Std. Error     1.213 (df = 37656)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 25: Regression results for Italy after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	-0.184	0.090	-17.19%	*
Before2	-0.193	0.110	-17.94%	
Before1	0.005	0.952	0.11%	
DivDay	0.130	0.075	13.34%	*
After1	0.060	0.633	5.69%	
After2	0.009	0.922	0.51%	
After3	-0.017	0.850	-2.09%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 26: Regression results for Luxembourg before bootstrap

Luxembourg

	Dependent variable:
	LogVolume
Before3	0.185**
	(0.083)
Before2	0.064
	(0.084)
Before1	0.098
	(0.084)
DivDay	0.050
	(0.084)
After1	0.101
	(0.084)
After2	-0.001
	(0.084)
After3	-0.043
	(0.084)
Observations	15,967
R2	0.887
Adjusted R2	0.886
Residual Std. Error	0.727 (df = 15895)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 27: Regression results for Luxembourg after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.185	0.045	19.86%	**
Before2	0.064	0.598	6.28%	
Before1	0.098	0.211	9.86%	
DivDay	0.050	0.584	4.75%	
After1	0.101	0.070	10.21%	*
After2	-0.001	0.979	-0.42%	
After3	-0.043	0.705	-4.57%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 28: Regression results for Netherlands before bootstrap

```
Netherlands
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                         0.018
                               (0.055)

Before2                         0.028
                               (0.056)

Before1                        -0.005
                               (0.055)

DivDay                          0.091
                               (0.056)

After1                          0.081
                               (0.056)

After2                         -0.104*
                               (0.056)

After3                        -0.123**
                               (0.056)

------------------------------------------------
Observations                   51,987
R2                              0.855
Adjusted R2                     0.855
Residual Std. Error      0.959 (df = 51747)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 29: Regression results for Netherlands after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.018	0.732	1.62%	
Before2	0.028	0.627	2.71%	
Before1	-0.005	0.931	-0.63%	
DivDay	0.091	0.067	9.38%	*
After1	0.081	0.256	8.30%	
After2	-0.104	0.066	-10.03%	*
After3	-0.123	0.064	-11.69%	*

Note: *p<0.1; **p<0.05; ***p<0.01

Table 30: Regression results for Norway before bootstrap

```
Norway
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                         -0.036
                                (0.070)

Before2                          0.024
                                (0.071)

Before1                          0.087
                                (0.072)

DivDay                          0.120*
                                (0.071)

After1                          0.169**
                                (0.070)

After2                          0.135*
                                (0.071)

After3                           0.074
                                (0.071)

------------------------------------------------
Observations                    33,840
R2                               0.833
Adjusted R2                      0.832
Residual Std. Error      0.984 (df = 33676)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 31: Regression results for Norway after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	-0.036	0.642	-3.82%	
Before2	0.024	0.410	2.12%	
Before1	0.087	0.211	8.84%	
DivDay	0.120	0.293	12.47%	
After1	0.169	0.092	18.16%	*
After2	0.135	0.063	14.15%	*
After3	0.074	0.456	7.37%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 32: Regression results for Portugal before bootstrap

```
Portugal
================================================
                        Dependent variable:
                    ----------------------------
                               LogVolume
------------------------------------------------
Before3                         -0.134
                                (0.156)

Before2                         -0.077
                                (0.156)

Before1                          0.213
                                (0.157)

DivDay                           0.108
                                (0.156)

After1                          0.319**
                                (0.156)

After2                           0.161
                                (0.160)

After3                           0.166
                                (0.156)

------------------------------------------------
Observations                     9,834
R2                               0.693
Adjusted R2                      0.692
Residual Std. Error      1.120 (df = 9778)
================================================
Note:                *p<0.1; **p<0.05; ***p<0.01
```

Table 33: Regression results for Portugal after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	-0.134	0.866	-13.56%	
Before2	-0.077	0.667	-8.56%	
Before1	0.213	0.657	22.25%	
DivDay	0.108	0.096	10.09%	*
After1	0.319	0.110	35.86%	
After2	0.161	0.096	15.00%	*
After3	0.166	0.316	16.69%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 34: Regression results for Russia before bootstrap

Russia

	Dependent variable:
	LogVolume
Before3	0.025
	(0.085)
Before2	0.126
	(0.085)
Before1	0.138
	(0.086)
DivDay	0.095
	(0.085)
After1	0.002
	(0.085)
After2	-0.006
	(0.085)
After3	-0.059
	(0.084)
Observations	27,167
R2	0.835
Adjusted R2	0.834
Residual Std. Error	0.991 (df = 27039)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 35: Regression results for Russia after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.025	0.722	2.16%	
Before2	0.126	0.209	13.02%	
Before1	0.138	0.087	14.33%	*
DivDay	0.095	0.275	9.61%	
After1	0.002	0.979	-0.16%	
After2	-0.006	0.883	-0.98%	
After3	-0.059	0.791	-6.03%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 36: Regression results for Spain

Spain

	Dependent variable:
	LogVolume
Before3	0.033
	(0.046)
Before2	0.046
	(0.042)
Before1	0.148***
	(0.047)
DivDay	0.240***
	(0.076)
After1	0.186**
	(0.079)
After2	0.166**
	(0.073)
After3	0.115**
	(0.052)
Observations	73,511
R2	0.852
Adjusted R2	0.851
Residual Std. Error	1.024 (df = 73148)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 37: Regression results for Sweden

Sweden

	Dependent variable:
	LogVolume
Before3	-0.049
	(0.071)
Before2	-0.028
	(0.089)
Before1	0.083
	(0.076)
DivDay	0.114**
	(0.054)
After1	0.193**
	(0.091)
After2	-0.079
	(0.101)
After3	-0.020
	(0.034)
Observations	65,140
R2	0.842
Adjusted R2	0.841
Residual Std. Error	1.119 (df = 64830)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 38: Regression results for Turkey before bootstrap

Turkey

	Dependent variable:
	LogVolume
Before3	0.239
	(0.176)
Before2	0.093
	(0.178)
Before1	-0.201
	(0.175)
DivDay	0.182
	(0.178)
After1	0.225
	(0.172)
After2	0.183
	(0.182)
After3	-0.061
	(0.180)
Observations	13,624
R2	0.840
Adjusted R2	0.839
Residual Std. Error	1.256 (df = 13541)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 39: Regression results for Turkey after bootstrap

Term	LogVolume	P-value	Percent	Significance
Before3	0.239	0.386	25.03%	
Before2	0.093	0.807	8.01%	
Before1	-0.201	0.527	-19.45%	
DivDay	0.182	0.588	18.05%	
After1	0.225	0.185	23.44%	
After2	0.183	0.421	18.09%	
After3	-0.061	0.196	-7.41%	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 40: Regression results for Switzerland

Switzerland

	Dependent variable:
	LogVolume
Before3	0.087
	(0.061)
Before2	0.045
	(0.065)
Before1	0.095*
	(0.053)
DivDay	0.095*
	(0.050)
After1	0.144**
	(0.065)
After2	0.142*
	(0.072)
After3	0.066
	(0.062)
Observations	66,061
R2	0.862
Adjusted R2	0.861
Residual Std. Error	0.912 (df = 65744)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 41: Regression results for UK

UK

	Dependent variable:
	LogVolume
Before3	0.046*
	(0.025)
Before2	0.089***
	(0.023)
Before1	0.139***
	(0.023)
DivDay	0.137***
	(0.039)
After1	0.102**
	(0.039)
After2	0.112***
	(0.033)
After3	0.050*
	(0.026)
Observations	278,979
R2	0.884
Adjusted R2	0.883
Residual Std. Error	1.040 (df = 277691)
Note:	*p<0.1; **p<0.05; ***p<0.01