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China's Import Ban, Waste Disposal and Fire Incidents in Italy

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Abstract

The study investigates the repercussions of China's 2018 plastic waste import ban on Italy's waste management system, focusing on how this policy shift influenced waste treatment volumes and the occurrence of waste-related fires. Employing a difference-in-difference empirical approach, the research wants to evaluate the impact of the policy shock on the amount of waste processed at Italian facilities and whether the increased waste pressure correlates with higher fire incidence near these sites. The analysis combines georeferenced data on fire events with facility-level treatment data and regional controls, covering the period from 2016 to 2020. Although the model has limitations, especially the lack of disaggregated plastic-specific data prevents a definitive causal claim, the findings indicate a significant and robust association between increased treated waste and the frequency of fires. The study also finds that a greater isolation of these facilities increases the results, regions with higher export capacity face fewer fire incidents, underscoring the burden imposed by export disruptions. These results highlight the broader economic and environmental consequences of global waste trade dependencies and stress the need for both, more resilient and sustainable trade partnerships and domestic waste management infrastructures.

Keywords: Waste, Waste Trade, Global Exports, Waste Fires, Pollution

J.E.L. classification: F13, F18, Q52, Q53, Q56

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Contents

1 Introduction

Plastics have become indispensable in modern life due to their versatility, durability, and safety, finding applications in areas ranging from packaging and consumer products to construction and healthcare. Their cost-effectiveness and flexibility have transformed industries, enabling innovations that were previously impossible. Over the past several decades, the production of plastics has undergone extraordinarily rapid growth, outpacing almost every other man-made material in terms of global output (Alam et al., 2018; Dilkes-Hoffman et al., 2019). This surge in production has led to the generation of massive amounts of plastic waste, with millions of tonnes produced annually.

The proliferation of plastic waste has posed a pressing challenge for global environmental management. Plastic materials are highly durable and resistant to natural degradation, which means that most plastic waste persists in the environment for decades or even centuries. Recycling has therefore become a critical component of efforts to reduce environmental impacts. Recycling plastic not only diminishes the demand for virgin polymers in industrial manufacturing but also lowers material costs, creating economic incentives for manufacturers. Recycled plastics have been particularly important in countries such as China, where they are extensively used in the manufacturing sector, supporting the nation's role as the world's largest producer and exporter of manufactured goods. In this context, China's demand for recycled plastics became a major driver of the global plastic waste trade, establishing the country as the primary destination for plastic waste generated in Europe, North America, and other regions.

According to the data presented by Brooks et al. (2018), over the past 25 years, China has taken in nearly 45.1% of the world's nonindustrial plastic waste amounting to roughly 106 million MT of plastic. China and Hong Kong together have accounted for 72.4% of global plastic waste imports. However, Hong Kong has largely served as a gateway, with the majority of its imported plastic waste, approximately 63% in 2016, being re-exported directly to China. While the global recycling trade has brought certain economic advantages to China (Qu et al., 2019), the massive influx of plastic waste has also had severe environmental consequences. In an effort to reduce pollution and improve environmental conditions (Wang et al., 2018), China introduced the National Sword policy in 2017 (Chinese General Administration of Customs, 2017), which imposed a permanent ban on the import of nonindustrial plastic waste starting in January 2018. This decision caused major disruption in the global plastic waste trade.

The domino effect triggered by China's 2018 ban on plastic waste imports exposed numerous flaws and weaknesses in the global plastic recycling system. Global exports dropped significantly in 2018, falling to half the volume recorded in 2016. Countries that had relied heavily on exporting their plastic waste were forced to confront systemic vulnerabilities in domestic waste management systems, including overcapacity, inefficiencies, and a lack of alternative recycling infrastructure.

The disruption of global waste flows also caused a significant shift in the international trade system, with Southeast Asian countries emerging as new primary recipients of plastic waste. These regions often lacked the stringent environmental regulations and processing infrastructure necessary to manage large volumes of imported plastics safely, raising concerns about environmental degradation and human health risks. Italy, for example, as one of the world's leading exporters of plastic waste, faced immediate challenges in redirecting its waste streams to new destinations, highlighting how deeply integrated and interdependent the global recycling trade had become.

The measure, introduced by China, specifically targeted plastic scraps, industrial waste, offcuts, and production residues. These materials have been rejected at Chinese customs, bringing to light critical flaws in the global plastic recycling system. Since the ban, plastic waste has become increasingly difficult to place on the international market. This disruption is alarming when considering that more than 90% of all plastic ever produced since the 1950s has never been recycled. Combined with the exponential growth in global plastic production in recent decades, the Chinese ban has significantly complicated waste management efforts worldwide.

Two major issues have emerged in the wake of the ban. First, much of the plastic waste once destined for China is now being rerouted to countries and regions with weaker environmental regulations. Many of these are located in Southeast Asia or other parts of the world that lack the legislative frameworks or the technological capacity to handle and properly recycle such waste. This has led to significant environmental and social concerns in these recipient countries. Second, on a global scale, plastic waste exports have decreased by roughly 50% between 2016 and 2018. As a result, countries that were previously large exporters of plastic waste are now faced with a growing surplus of materials that their domestic systems are ill-equipped to manage. Reports of overwhelmed collection systems, recycling disruptions, and the redirection of recyclable materials to landfills or incinerators have become increasingly common.In Italy, these global challenges are mirrored and intensified by a troubling rise in fires at waste storage facilities, especially those handling plastic. Many of these incidents are believed to be linked to waste over-accumulation, which further highlights the urgency of addressing the root causes of the plastic crisis at both national and international levels.

This research aims to analyze Italy's waste export trends with its key trading partners, in order to elucidate the complexity of the waste value chain. Furthermore, it seeks to examine the potential relationship between the volume of waste processed by treatment plants or landfills within Italy and the spatial occurrence of waste-related fires, considering these incidents as possible negative externalities arising from disruptions in the waste supply chain. The analysis is carried out over time, from 2016 to 2020, so that it could be possible to evaluate the impact of the Chinese ban on the waste fire effect. This study builds on the little body of literature on plastic waste trade and waste exports, particularly the impact of China's ban on plastic waste imports. However, it introduces an innovative perspective by focusing on the potential link between Italian waste flows to other countries and the occurrence of waste-related fires. While grounded in environmental concerns, the study remains firmly within the field of economics. Its ultimate objective is not merely to evaluate the environmental shortcomings of poor waste management, but to analyze the broader economic consequences that may arise. By examining these environmental shocks through the lens of economic performance, the research aims to shed light on how underlying structural issues in global waste trade can trigger localized pollution events with significant implications for public health and economic activity.

Firstly, in order to provide a comprehensive background on the dynamics of the international plastic waste trade, the study includes a dedicated section that analyzes the evolution of global, but mainly Italian waste exports to various partner countries. This section presents a detailed overview of the trends in total and plastic waste exports from Italy over the period 2014–2023, highlighting the significant disruptions caused by China's 2018 import ban. By examining export flows both within the EU and to non-EU countries, such as Malaysia, Vietnam, Turkey, and Indonesia, the analysis reveals how Italy's waste trade network was forced to reorganize in response to shifting global regulations. The empirical evidence is supported by visual representations, which illustrate the redirection of plastic waste exports toward new destinations following the closure of the Chinese market. This contextual foundation is essential to understand the pressure placed on domestic waste treatment systems and the potential link to the rise in waste-related fires within Italy.

Finally, in the empirical analysis, the study integrates georeferenced data on waste fires, sourced from a parliamentary inquiry, alongside facility-level data from ISPRA on waste treatment, localization, and typology. To ensure analytical consistency, the dataset was built through a systematic process of collection, classification, and refinement of these heterogeneous sources. Fire events were first identified and categorized according to the type of facility involved, and then carefully cross-checked to eliminate duplicates and inconsistencies. Additional records from fire department intervention maps were integrated, while non-relevant incidents were excluded. This process of cleaning, normalization, and standardization transformed fragmented and uneven information into a coherent dataset, providing a reliable empirical basis for the analyses presented in this study. Data on different types of waste facilities were then collected to establish a link between each facility, its treatment capacity, and the nearest fire event. The research distinguishes between various categories of fires and facility types. It further includes regional control variables such as waste export ratios, waste production levels and population density per region.

To assess the impact of the policy shock, the study relies on two complementary strategies. First, a difference-in-differences approach is implemented to compare the incidence of fires before and after the Chinese ban, exploiting variation in exposure linked to the amount of waste treated. The results of this specification, however, are weak and provide limited explanatory power. Therefore, the analysis proceeds with a second strategy that more directly captures the mechanisms at play: firstly looking only at the impact of the Chinese ban on the volume of waste processed in Italian plants. Later, the relationship between processed waste volumes and the frequency of fires near waste facilities is analyzed through a negative binomial model, which accounts for both overdispersion and the large share of zero-fire observations.

The analysis shows that the 2018 import ban triggered a significant increase in domestic waste treatment volumes, aligned with a concurrent increase in fire events in treatment facilities. Although limitations in data disaggregation prevent a precise attribution of effects to plastic waste specifically, the econometric results consistently indicate a positive and statistically significant association between treated volumes and fire frequency. In particular, estimates from negative binomial model demonstrate that increases in treatment loads are systematically associated with higher expected counts of fire incidents. Moreover, control variables provide further insights: the export ratio exhibits a strong negative correlation with fire occurrence, suggesting that regions with greater capacity to redirect waste abroad are less exposed to domestic system overloads, while facility isolation is positively associated with risk. Overall, the findings reveal structural weaknesses in Italy's waste management system, with the disruption of international trade flows exacerbating inefficiencies and amplifying environmental and public health hazards.

As a final component of this research, attention is directed to the evolution of particulate matter (PM) emissions in Italy over time. The objective is to examine how emissions have varied across different source sectors, thereby identifying both progress and persistent challenges. While several categories show a marked decline in PM emissions, those associated with fire events appear comparatively stable, with limited reductions relative to other sources. This observation highlights the need to further investigate the specific role of fire-related emissions in shaping air quality dynamics. Framing the issue in this way also lays the groundwork for subsequent analyses of how such emissions, with a special attention to waste fire events, may influence broader economic negative outcomes.

Despite the limitations of data aggregation, particularly, the lack of plastic-specific waste processing figures, the analysis reveals a significant association between increased treatment volumes and fire occurrences, especially following the disruption caused by China's policy. The study contributes to the broader literature on global waste trade, environmental externalities, and supply chain resilience, offering an economic perspective on the localized consequences of international regulatory changes.

2 Literature Review

The trade of waste, as well as domestic waste management, and the effects on air pollution are pressing environmental challenges, with far-reaching implications not only for ecosystems but also for human health, productive systems, and labor markets. Recent literature highlights how globalization has amplified these issues, interweaving environmental and economic dynamics into increasingly complex and interdependent networks. On one hand, the global trade of plastic waste has redistributed the burdens and benefits of waste management between developed and emerging economies, sparking debates over the efficiency, equity and sustainability of such practices. On the other hand, air pollution, enhanced by extreme events such as wildfires or waste fires, raises concerns not only for public health but also for productivity and labor market participation.

In this context, the analysis of international plastic waste trade networks and the consequences of China's recent import restrictions, have triggered a profound reorganization of global trade flows. The importance of resilience and stability in global supply chains in the face of environmental shocks and policy disruptions. Insights from this line of research suggest that coordinated international action and the design of optimal policies are necessary to safeguard economic interdependence and social welfare. On the other hand, studies on air pollution have revealed its impact on both health outcomes and economic indicators, showing that the hidden costs of pollution extend well beyond ecological damage. Taken together, this body of research underscores the need for an integrated, multidisciplinary approach to environmental policy, one that accounts not only for ecological concerns but also for economic and social consequences.

2.1 Waste Trade Networks

The literature on the global plastic waste trade has evaluated the impact of China's plastic import ban. In particular, Brooks et al. (2018) and Tan et al. (2025) studied the historical trade of plastic waste. Brooks et al. (2018) evaluated the impact of China's import ban using linear regression, estimating that

111 million metric tons of plastic waste would be displaced by 2030. The studies by Velis (2014) and and Ruceskva et al. (2017) shows the major role of China in global plastic waste recycling markets. Another study by Marrs et al. (2019) argues trasboundary trade in plastic waste discussing the phenomenon of developed countries often inflating recycling rates by exporting plastic waste to emerging economies, where limited infrastructure leads to high mismanagement and environmental pollution pointed to the illegal behavior occurring throughout the value chain in the global plastic waste trade.

Additionally, Wang et al. (2019) apply the complex network method to quantitatively describe the spatiotemporal evolution of global plastic waste trade networks (GPWTNs) and to explore the impact of China's plastic import ban on the global plastic waste trade. The results reveal that global plastic waste trade is a complex, unequal, and increasingly unstable network dominated by a few key players, most notably China, and highlights that China's import ban has triggered a major redistribution of trade flows, underscoring the urgent need for coordinated international policies, stronger waste management systems, and shared responsibility across both exporting and importing nations. Xu et al. (2024) as well, emphasizes the complexity of waste plastic management and the importance of global cooperation, providing evidence of the growing role of smaller European exporters and increased intra-regional trade, following the China ban.

Regarding plastic waste production, Geyer et al. (2017) asserts that 79% was accumulated in landfills or the natural environment. If current production and waste management trends continue, roughly 12,000 Mt of plastic waste will be in landfills or in the natural environment by 2050. This supports the relevance that plastic waste trade has, despite its issues; Li et al. (2024) shows that trade results in lower environmental impacts than treating domestically. These findings underscore the significance of recognizing plastic waste trade and the need for countries to improve their internal management infrastructures.

2.2 Supply Chain Resilience

Moreover, further studies on the topic would contribute to the growing discourse on supply chain resilience. Supply chain disruptions are becoming more and more recurrent and can depend on different causes; natural disasters, geopolitical disputes, transportation failures, cyberattacks. The link between supply shortages and global trade has prompted policymakers and the public to reconsider current models, raising questions about whether firms should diversify suppliers or reshore parts of their supply chains to reduce disruption risks. This debate around supply chain vulnerability is closely connected to the global waste industry, in light of China's 2017 plastic waste import ban. This acted as a major supply chain shock, disrupting a deeply interconnected and geographically dispersed waste trade system. When key nodes like China exit the system, the repercussions expose the fragility of global dependencies and highlight the urgent need for more resilient, transparent, and sustainable trade waste structures and local implants. In this context, Baldwin and Freeman (2022) reviews studies that look at risks to and from global supply chains (GSCs) and at how they have recovered from past shocks, to understand whether shortages would have been less severe if GSCs had been either shorter and more domestic or more diversified. The paper by Grossman et al. (2023) develops a framework to identify and quantify the discrepancies between social and private valuations in global value chains, using these to analyze optimal (first-best) and constrained (second-best) policy responses to supply chain inefficiencies and disruptions, with a focus on the asymmetric costs and risks inherent in international trade of intermediate goods.

A recent contribution by Matsuyama (2017) broadens the understanding of the demand side of structural change. The study demonstrates how Engel's Law shapes long-run patterns of employment, innovation, productivity growth, and trade. Using a two-country model with directed technical change, he shows that globalization does not homogenize demand but instead amplifies domestic demand heterogeneity as a driver of structural change.

These works are based on the early literature on trade policy under the threat of embargoes developed several distinct but complementary lines of inquiry. Mayer (1977) examines a country's optimal trade policy under the threat of embargoes or trade disruptions, showing that a production subsidy on the imported good is the best option and that even a tariff can be justified on economic efficiency grounds. Another foundational contribution was by Bhagwati and Srinivasan (1976) who formalized the idea that the probability of a trade disruption could depend on the volume of trade itself. Their approach was to examine the nature of optimal policy intervention required in the exporting country when there is the possibility that the importing country invokes a market disruption-induced trade restriction.

Building on this logic, Arad and Hillman (1979) extended the analysis to incorporate dynamic considerations, specifically learning-by-doing in the production of goods that might later be subject to embargoes. This extension highlighted how protective measures could have long-run efficiency implications by sustaining domestic production capabilities in the face of uncertain trade relations. Finally, Cheng (1989) contributed by modeling embargo threats as recurrent and stochastic events, formalized as a two-state stationary Markov process. Importantly, his framework incorporated constraints on the speed of inter-sectoral reallocation, thereby capturing adjustment frictions that shape the effectiveness of different policy responses. In doing so, Cheng (1989) provided a richer and more realistic characterization of how economies adjust under persistent threats of embargoes.

2.3 Air Pollution and Labor Outcomes

Some previous studies explore how large-scale pollution events, such as fires, can affect local air and soil quality, and impact, for instance, firm productivity and labor outcomes. Wildfire smoke, like other forms of air pollution, contains particulate matter that enters the lungs and can pass into the bloodstream. Smoke also carries other pollutants, such as ozone, carbon monoxide, atmospheric mercury, and a variety of volatile organic compounds (VOCs). A large literature in the biomedical sciences, public health and economics demonstrates the negative effects of exposure to air pollution on human health (Deryugina et al., 2019). Although wildfire smoke is understood to operate through the same channels as other sources of air pollution, the composition of wildfire smoke may be more or less harmful to human health per unit of measured particulate matter [1]. Studies of the health effects of wildfire smoke have linked exposure to increases in adult mortality (Miller et al., 2021), increases in

[1]Research comparing the composition of smoke from biomass burning and car exhaust shows that smoke contains more reactive VOCs. This higher reactivity is consistent with the fact that fires involve less complete combustion of carbon materials than internal combustion engines (e.g., Verma et al., 2009; Bates et al. (2015)).

infant mortality (Jayachandran, 2009)and elevated risk of low birth weight (McCoy and Zhao, 2016).

Air pollution has been shown to affect outcomes beyond health (Aguilar-Gomez et al., 2022). Individuals often respond to poor air quality by taking costly precautionary measures, such as staying indoors. In the case of wildfire smoke, the evidence from surveys highlights a range of behavioral adjustments, including avoiding outdoor activities, missing work, and increasing indoor air filtration (Jones et al., 2015). Burke et al. (2021) further documents widespread changes in awareness, mobility, health-related behavior, and emotional response in the face of increased exposure to wildfire smoke. A growing body of economic research also finds that air pollution can reduce worker productivity and lead to more frequent absenteeism [2].

The paper by Borgschulte et al. (2022), for instance, studies how air pollution impacts the US labor market by analyzing effects of drifting wildfire smoke. They link satellite smoke plumes with labor market outcomes to estimate that an additional day of smoke exposure reduces quarterly earnings by about 0.1 percent. Extensive margin responses, including employment reductions and labor force exits, can explain 13% of the overall earnings losses. Quantifying the broader effects of air pollution on labor market outcomes is of great importance for understanding how pollution affects human welfare and designing optimal air quality policies. There is still an evident failure to consider labor market costs, and therefore may lead to inefficient pollution standards and regulations.

3 International Waste Trade

3.1 The Global Situation

For many Asian countries[3], importing plastic waste presents an economic opportunity, as large volumes of this waste have market value. Unlike the European Union, these countries often have less stringent regulations governing waste treatment, allowing for more relaxed and less controlled management practices. This regulatory gap creates an incentive to accept foreign plastic waste despite environmental risks.

Awareness of the challenges of plastic waste management has developed more recently than for materials such as paper, glass, and metals. The EU still lacks the full capacity to reuse, recycle, or recover all its plastic waste, leading to great amounts of exports. Various factors influence the scale and destination of plastic waste exports from the EU. These include tariff and non-tariff trade barriers, differences in treatment costs, transport expenses, environmental taxes, policy stringency, available treatment infrastructure, and how waste is classified under national and international legislation.

However, the global handling of plastic waste is far from sustainable. Much of it is improperly managed, dumped on land, burned, or washed into oceans, resulting in severe ecological damage. Part of this damage will be analyzed in this research, and its importance is also related to the several direct and indirect economic repercussions. Plastic pollution is a growing threat to marine life, as animals often ingest plastic or become entangled in it. Microplastics, in particular, pose a risk to human health by entering the food chain through seafood consumption. Beyond this, plastic has a significant carbon

[2] See Hanna and Oliva (2015) and Aragon et al. (2017) for air pollution effects on hours worked; Holub et al. (2020) for sick leave; Chang et al. (2016) for the productivity of agricultural workers.

[3] "The plastic waste trade in the circular economy", Briefing no. 7/2019, European Environment Agency.

footprint. Its production is heavily dependent on fossil fuels, with emissions comparable to those of the aviation industry. When plastic waste is incinerated or decomposes in landfills, it releases greenhouse gases, further contributing to climate change.

Alarmingly, global recycling efforts have been insufficient. Of the approximately 6.3 billion tonnes of plastic waste generated between 1950 and 2015; less than 10% was recycled, more than 60% have ended up in landfills or the natural environment, the rest incinerated or unaccounted for. Once released into the environment, plastic can persist for centuries, disrupting ecosystems and reducing biodiversity by damaging the natural services that support life.

Export of plastic waste to China has historically grown alongside the country's rising plastic production and consumption. Initially, much of this waste was handled by small, informal facilities lacking adequate regulation or standards. However, China has started transitioning to larger, more regulated plants with improved environmental and quality controls. Meanwhile, many countries that receive plastic waste from the EU still have underdeveloped waste management systems. In these regions, imported waste is often handled unsafely: dumped, openly burned, or processed without oversight. This happens despite EU regulations requiring treatment under conditions comparable to those within the EU. Weak governance and a shortage of licensed operators in parts of Southeast Asia have led to widespread misuse and environmental harm.

Moreover, the theory of ecologically unequal exchange suggests that global political-economic factors, especially the structure of international trade, shape the unequal distribution of environmental harms and human development; wealthier and more powerful Global North nations have disproportionate access to both natural resources and sink capacity for waste in Global South nations[4]. Bai and Givens (2021) provides nuanced evidence of ecologically unequal exchange relationships between high-income countries and non-high-income countries in plastic waste trade. The results indicate that higher plastic waste import is associated with lower economic development in non-high-income countries.

Given the limited transparency over how exported waste is managed, there is growing recognition that the EU should process more of its plastic waste domestically. Building internal capacity for recycling and reuse not only supports better environmental outcomes, but also ensures Europe takes full responsibility for managing its own waste sustainably.

As clearly explained in the European Environment Agency briefing *The plastic waste trade in the circular economy*, between January 2017 and April 2019, there was a significant shift and decline in the volume of plastic waste exported from the EU-28 to non-EU countries (Figure 1). This change was largely driven by China's implementation of strict import restrictions. Consequently, exports to China and Hong Kong dropped sharply, prompting a redirection of plastic waste flows to alternative countries.

[4]Givens et al. (2019)

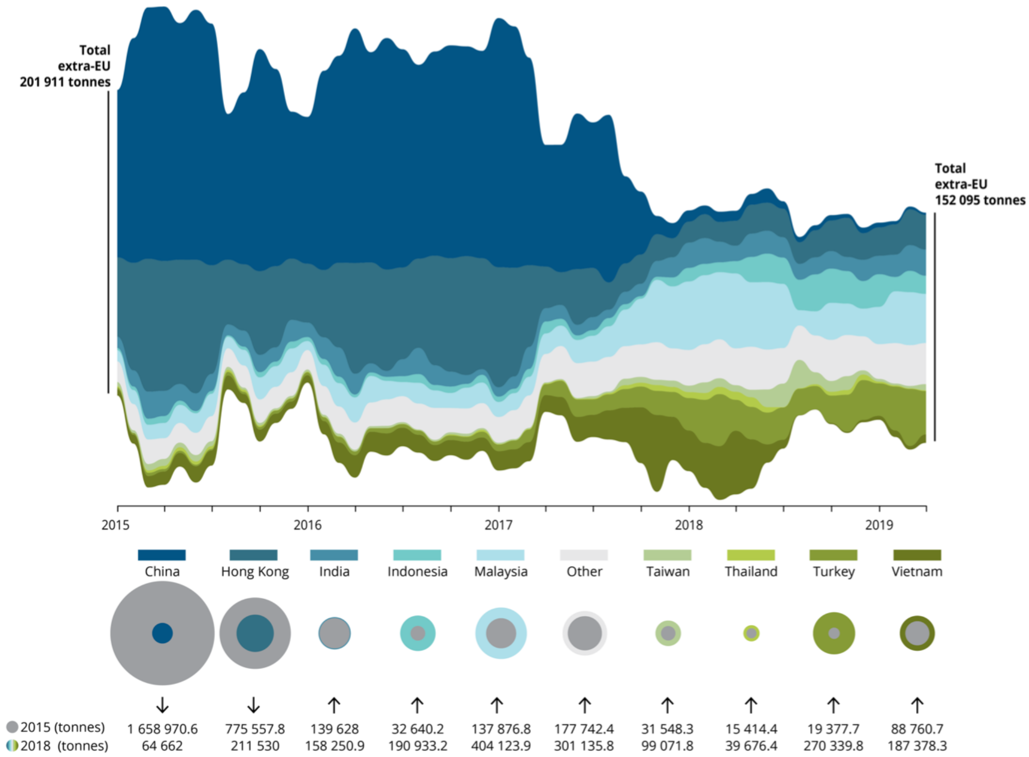

Figure 1: Extra-EU-28 plastic waste trade by receiving country. Source: European Environment Agency briefing *The plastic waste trade in the circular economy* using Eurostat data.

Another conclusion suggested in the report is that the decreasing trend of plastic waste export is likely to result in an increase in incineration and landfilling in the short term, due of the current lack of capacity to increase recycling and reuse in the EU. As stated previously, the aim of this research is to find evidence in the data of landfill overcapacity and the consequent increase of waste-related fires in Italy.

For a comprehensive overview of global and Italian plastic waste routes, particularly the trade shifts triggered by China's import ban, the Greenpeace report *The Global and Italian Plastic Waste's Routes* serves as a valuable reference. According to the report, following China's import ban on plastic waste, Southeast Asian countries, particularly Malaysia, Vietnam, and Thailand, rapidly became the main global destinations for plastic waste shipments. This shift occurred between mid-2017 and mid-2018 as exporters sought alternatives to the Chinese market. However, these countries soon found themselves overwhelmed by the volume of imports and, by mid-2018, introduced their own restrictions to curb the influx. As a result, global plastic waste exports, primarily from the United States, Germany, the United Kingdom, and Japan, began shifting toward other nations, notably Indonesia and Turkey, which remain among the largest importers today.

The loss of China's major market triggered a dramatic contraction in global plastic waste flows. By the end of 2018, total exports had dropped by nearly 50% compared to 2016 levels. A significant factor in this decline was the sharp reduction in volumes passing through Hong Kong to other Southeast Asian nations during the first months of 2018. Despite efforts to redirect waste to other regions, new importing countries such as India, Taiwan, South Korea, Turkey, and Indonesia, were unable to fully absorb the quantities previously destined for China.

3.2 Italy's Partners in the Total and Plastic Waste Trade

According to Greenpeace's international report[5], Italy ranked 11th among the world's plastic waste exporters, contributing 2.25% of total exports. Only in 2018, Italy exported around 200 thousands tonnes of plastic waste, precisely 197 thousands. The top five importing countries were Malaysia (15.7%), Thailand (8.1%), Vietnam (7.6%), Hong Kong (6.8%), and the United States (6.1%). The rapid rise and fall of Southeast Asia's role in this trade underline the fragility and volatility of the global plastic waste market in the wake of China's policy shift. Exports to Europe are also expanding, with Romania gaining increasing importance and Slovenia maintaining a consistently significant role.

This section provides a concise overview of the evolution of Italy's total and plastic waste exports, with a focus on their distribution across global destinations, including EU member states, non-EU countries, and key international waste trade partners.

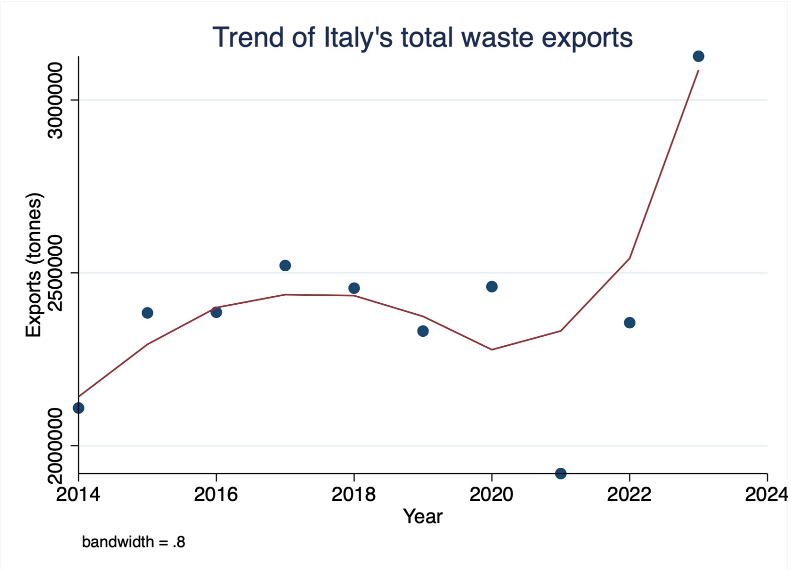

Figure 2: Total amount of Italy's waste export from 2014 to 2023. Each dot represents the actual annual export volume, while the line shows a smoothed trend using a locally weighted regression with a bandwidth of 0.8 representing italian total waste's exports towards the world (source: Eurostat).

Firstly, the above graphs illustrate the trend in Italy's total amount of waste and plastic waste exports from 2014 to 2023, measured in tonnes. Each dot represents the actual annual export volume, while the line shows a smoothed trend using a locally weighted regression with a bandwidth of 0.8. In Figure 2, the trend indicates a general increase in waste exports that slows down until 2018, and a decline around 2019–2020. After that, a greater increase is observed toward 2023. The slight dip around 2017 aligns with the effects of the China ban and broader uncertainties in the global waste trade system, which persisted for several years. The sharp increase in exports after 2021 may indicate a reorganization and a more stable network of international waste trade partnerships.

Comparing Figures 2 and 3, it is evident that Italy's total waste exports to the rest of the world were less severely impacted by the China ban, while plastic waste exports experienced a sharp and

[5] https://www.greenpeace.org/static/planet4-eastasia-stateless/2020/06/9858a41c-gpea-plastic-waste-trade-research-briefing-v2.pdf

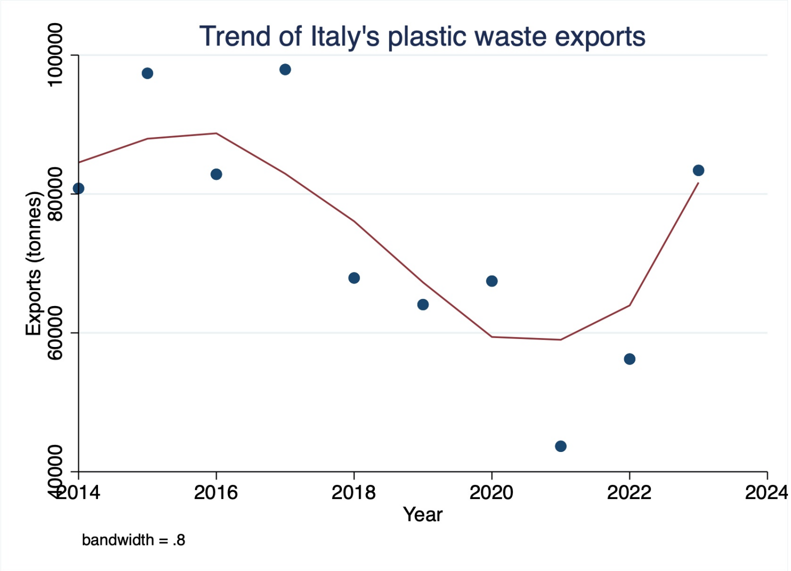

Figure 3: Amount of Italy's plastic waste export from 2014 to 2023. Each dot represents the actual annual export volume, while the line shows a smoothed trend using a locally weighted regression with a bandwidth of 0.8 representing italian plastic waste's exports towards the world (source: Eurostat).

immediate decline. The effect of the import restrictions is clear, particularly in the case of plastics, where exports dropped significantly, indicating a lack of alternative destinations in the short term. It is mainly because of this evident problem that this research's aim is to look into possible effects in Italy's waste management in loco, such as the increase of waste fires close to waste implants. In contrast, the total waste trend of exports appears to flatten during this period, suggesting a temporary stagnation rather than a collapse. After 2021, both trends show a notable recovery, implying a reconfiguration of Italy's waste export system. The renewed growth in plastic waste exports likely played a key role in sustaining the larger increase in total waste exports, pointing to the successful establishment of new international partnerships following China's withdrawal from the global plastic waste trade.

The two graphs in Figure 4 displays the trends in Italy's waste exports to EU and non-EU (Extra-EU27) countries, using locally weighted scatterplot smoothing to illustrate general patterns.

In the first figure, focusing on plastic waste exports, there is a clear divergence between exports to Extra-EU27 and Intra-EU27 countries. While exports within the EU (Intra-EU27) remain relatively stable and even show a slight increase until 2020 before declining, exports to non-EU countries sharply decrease after 2016, reflecting the impact of China's import restrictions which gradually started that year. After 2021, a moderate recovery is observed, suggesting the establishment of alternative export markets outside the EU.

In contrast to plastic waste, total exports to Extra-EU27 countries demonstrate only a modest decline following 2017, without the pronounced collapse observed in plastic waste. After 2021, total waste exports experience significant growth, driven both by a broader reorganization of Italy's waste trade networks and by the recovery of plastic waste exports. Meanwhile, exports within the EU gradually decline over the entire period.

Finally, to provide a more detailed analysis of Italy's waste trade relationships, the graphs below illustrate trends in total and plastic waste exports to selected destination countries: China, Thailand, Vietnam, Malaysia, and Turkey. In particular, Thailand, Vietnam, Malaysia, and Turkey have been

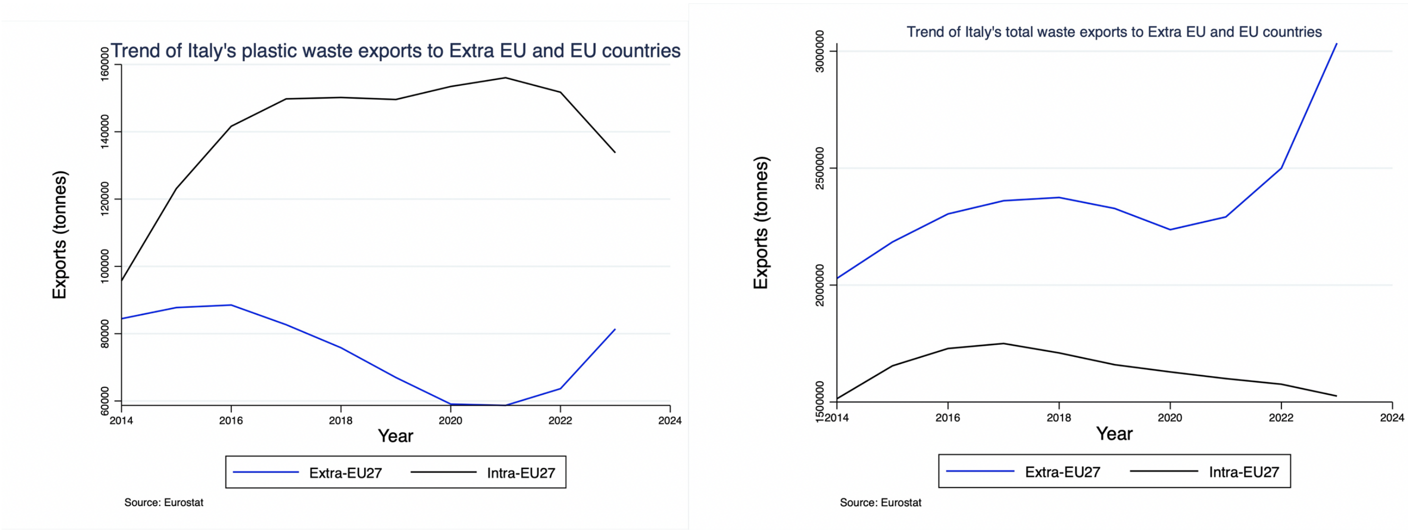

Figure 4: Trends in Italy's exports of plastic waste and total waste, showing the distinction between destinations within the European Union and those outside the EU. The figure highlights differences in export dynamics depending on the geographical area of destination.

identified by the Greenpeace report as the main alternative trade partners following China's import ban outside Europe.

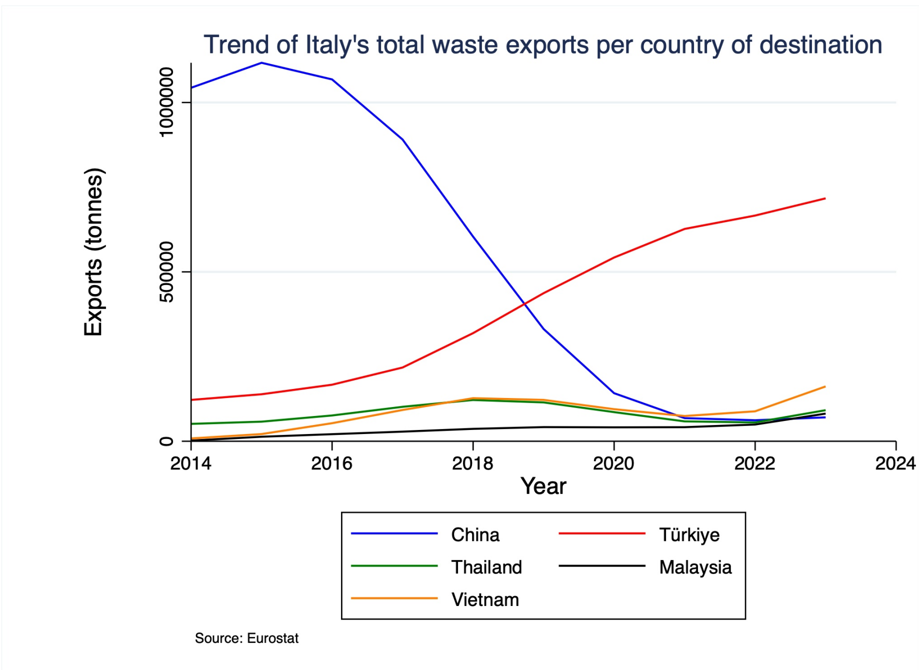

Figure 5: Trend of Italy's total waste exports per country of destination: China, Turkiye, Thailand, Malaysia and Vietnam.

Concerning total waste exports, China was initially the dominant recipient, with exports peaking at over 1 million tonnes around 2015. However, following a sharp decline after 2017 exports to China almost disappeared by 2020. Concerning Italian waste, together with the plastic import ban also a strong reduction in total waste imports happened in China. At the same time, Turkey absorbed much of the redirected waste, with its imports steadily increasing to approximately 800,000 tonnes by 2023. In contrast, Malaysia, Thailand, and Vietnam registered only modest increases, remaining relatively

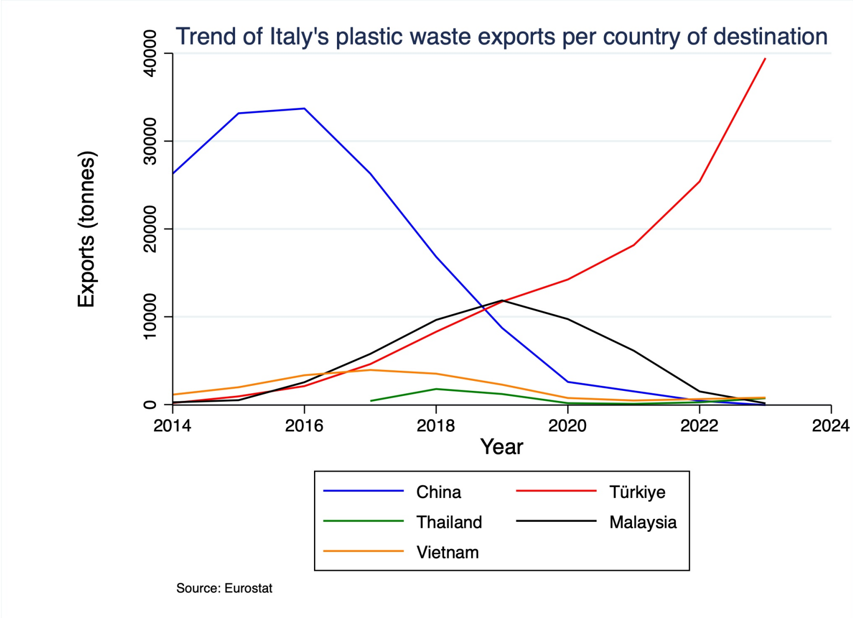

Figure 6: Trend of Italy's plastic waste exports per country of destination: China, Turkiye, Thailand, Malaysia and Vietnam.

minor destinations throughout the period. The role of this countries is slightly more evident looking only at plastic waste exports.

The second graph, Figure 6 focusing on plastic waste exports, presents a similar trend. Again, China was initially the primary destination, reaching a peak of over 30,000 tonnes before 2017. Following the decline in exports to China, Turkey experienced a notable rise, becoming the principal destination for Italian plastic waste by 2023, surpassing 40,000 tonnes. Malaysia also recorded a temporary increase between 2017 and 2020, although exports later decreased. Thailand and Vietnam, experienced the same growth, but continued to receive comparatively minor volumes.

An analysis of plastic waste exports reveals that Southeast Asian countries initially became key trade partners in the immediate aftermath of China's import ban, as demonstrated by the increase in export volumes after 2017. Nevertheless, this change was temporary: by 2020, more evidently in the case of Malaysia, exports to these countries declined, following the implementation of their own restrictions on plastic waste imports driven by environmental concerns. At the same time, the overall volume of Italy's plastic waste exports continued to rise at an accelerated rate, confirming Turkey as the principal trade partner. This pattern of evolution is especially pronounced when considering plastic waste exports exclusively.

To complete the discussion about Italy's waste export destinations, additional trends are presented for other major importing countries. In this final set of graphs, China and Turkey are excluded to better highlight dynamics among the remaining relevant destinations.

Figure 7 illustrates the trajectory of total waste exports. Indonesia stands out with a substantial increase until 2020, peaking at over 450,000 tonnes, followed by a noticeable decline. This dynamic suggests a shift in bilateral trade flows, potentially driven by tightening environmental regulations. Still, Indonesia after 2017 was probably the main partner for total waste exports after China's import stop. Following the restrictions implemented by Malaysia and Vietnam around 2018–2019, as documented in the earlier figures, Indonesia emerged as a major global importer of waste. Although

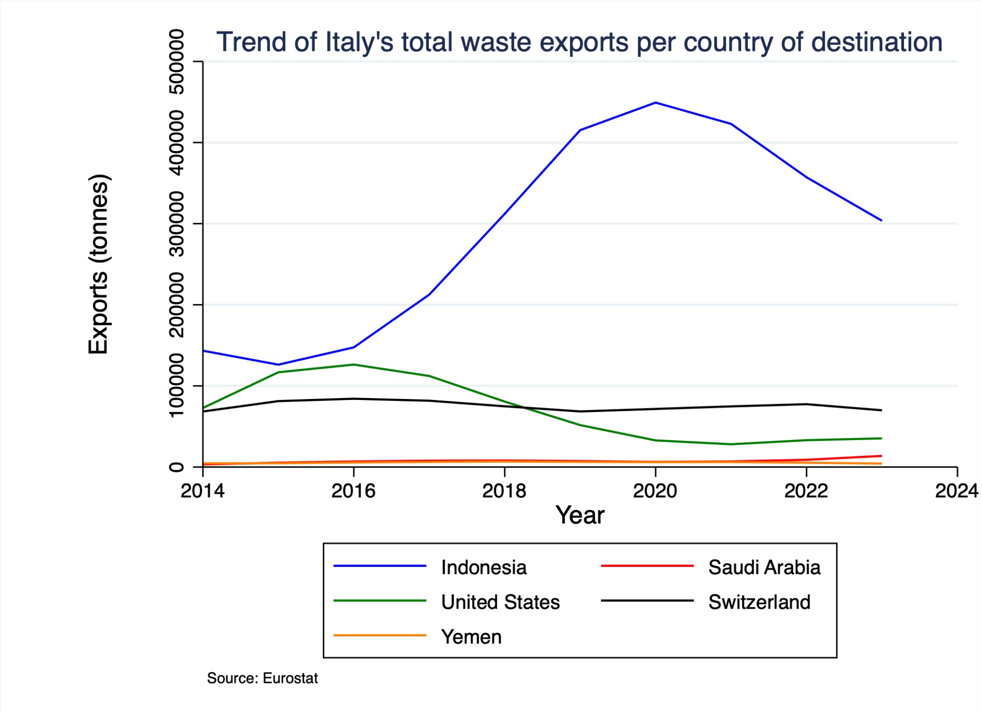

Figure 7: Trend of Italy's total waste exports per country of destination: Indonesia, Saudi Arabia, United States, Switzerland and Yemen.

this goes beyond the interest of this study and the focus on Italy, it is worth noting that Indonesia's broader relevance in the global waste market intensified in this period. Italy's exports to Indonesia already grew significantly starting in 2016.

In contrast, the United States experiences a gradual decline in waste imports from Italy after 2017. Switzerland shows a more stable trend, with volumes remaining between 60,000 and 90,000 tonnes, hinting at a relatively constant and possibly institutionalized trade flow. Meanwhile, Saudi Arabia and Yemen appear to be marginal recipients, with consistently lower export volumes throughout the period.

The roles of Saudi Arabia and Yemen change when analyzing plastic waste exports specifically (Figure 8). Saudi Arabia shows a sharp increase in recent years, becoming the most prominent destination by 2023, suggesting a potential shift in Italy's export structure for plastic waste. This is consistent if considering the other restrictions that followed China's import ban: firstly Malaysia and Thailand and then, also, Indonesia. Yemen, on the contrary, displays a steady increase during the years surrounding China's waste import ban, implying its potential emergence as a substitute destination during this transition. The United States maintains a leading, worth mentioning position among these countries, although with fluctuations: a decline between 2014 and 2018 is followed by a recovery through 2022. Switzerland records a gradual but steady increase in imports, which may reflect growing processing capabilities or evolving trade agreements, while Indonesia remains relatively marginal compared to its prominence in total waste. This highlights distinct country-specific preferences or regulatory frameworks governing different waste categories.

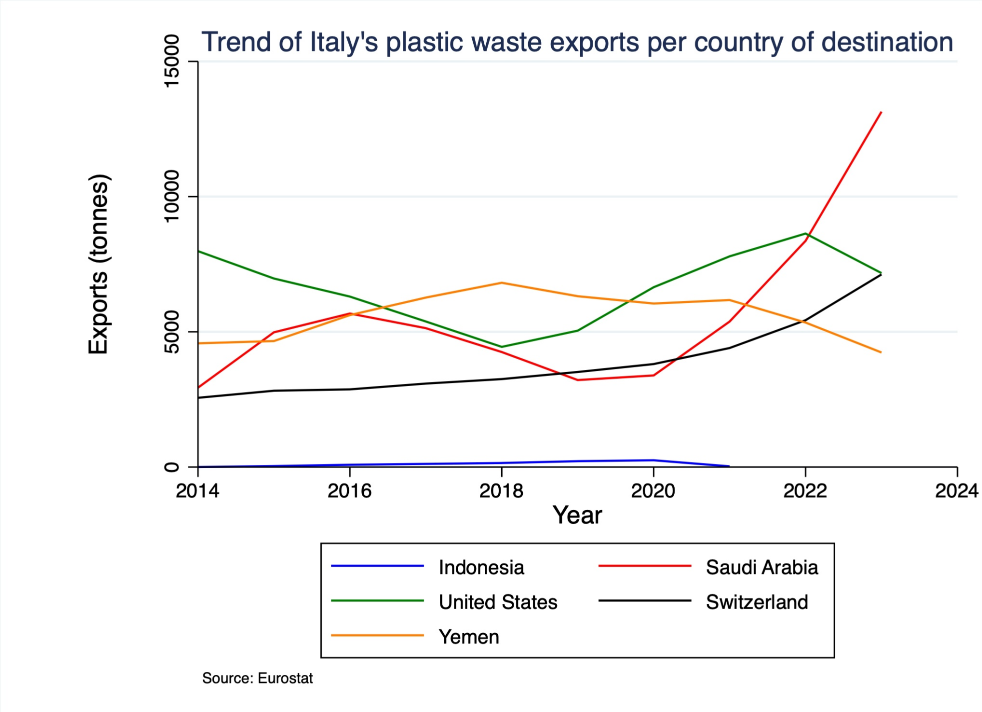

Figure 8: Trend of Italy's plastic waste exports per country of destination: Indonesia, Saudi Arabia, United States, Switzerland and Yemen.

3.3 Policy and Conceptual Framework

According to Eurostat data, Italy has consistently exported about one-third of its plastic waste outside the European Union. These exports, theoretically intended for recycling, must comply with EU Regulation No. 1013/2006[6], which mandates that waste can only be exported to countries where it will be treated under environmental and health standards equivalent to those of the EU. However, in practice, there are concerns about the actual compliance with these requirements. Past incidents, such as exports to China involving false certifications, highlight the risk of organized illegal waste trafficking.

Following China's import restrictions, as it was shown, new export routes have emerged. A significant volume of Italian plastic waste is now sent to other EU countries, including Austria, Germany, and Spain, which collectively account for over 40% of such exports. There has also been a marked increase in exports to Romania and a stable, significant flow to Slovenia. Some operators have established facilities in Slovenia and use them as transit points for further global exports. This has created concerns about the effectiveness of environmental controls in newer EU member states. Despite initial disruptions, the waste export system continues to facilitate shipments beyond Europe, and often under questionable regulatory compliance.

Among these destinations, Turkey deserves particular attention due to the scale of the imports and the environmental risks involved. Today Turkey imports around 12 thousands tonnes of plastic waste each month. The spike in plastic waste exports, as said, followed China's decision to ban the import of plastic waste, and especially the other countries, such as Malaysia, Thailand and Vietnam, that implemented similar restrictions. As a result, Turkey increasingly became the destination for a significant and poorly regulated influx of plastic waste shipments. Several independent investigations

[6]https://eur-lex.europa.eu/legal-content/it/TXT/?uri=CELEX:32006R1013.

by Greenpeace, in the recent years, have documented open-air landfills in Turkey filled with Italian waste, which are contaminating soil and water in several regions. During the past decade, Italian plastic waste exports to Turkey have surged from around 440 tonnes to more than 41,000 tonnes, making it the leading non-EU destination. The inclusion of Turkey in the OECD is an essential condition that allows waste exports under EU Regulation No. 1013/2006; despite this, the actual treatment of imported plastic waste in the country often fails to meet environmental standards equivalent to those of the EU.

4 Data

This analysis relies on a nationwide linkage of data on waste fires exposure and data on landfills and waste facilities. These data derive from a variety of sources, this section describes the construction of the database and the definitions of key variables used in the analysis and cover the period 2016-2020.

4.1 Waste Fires

The initial data on fires in waste collection and management facilities were sourced from the georeferenced map ”INCENDI IMPIANTI RIFIUTI” curated by Claudia Mannino, a deputy of the 17th Legislature of the Federation of the Italian Green Party. The fires reported on this map refer each to a news article that provides the date, location, and subject of the fire (whether it involves waste fires or facilities managing waste disposal). The construction of the map was contextual to the parliamentary inquiry into illegal activities connected to the waste cycle and related Environmental Offenses[7]. Fires have played a central role in the environmental and criminal dynamics investigated in the parliamentary inquiry. These acts are frequently tied to organized crime networks that exploit the legal and institutional weaknesses surrounding environmental protection. The inquiry highlights how malicious burning not only contributes to ecological degradation and biodiversity loss, but also acts as a gateway to further illegal activities, such as unauthorized waste disposal and speculative land development. In this context, fire emerges not merely as a destructive force, but as a calculated tool in broader schemes of environmental crime.

In the creation of the dataset, the data were categorized as waste-related fires based on the type of facility involved. The category *Fires in Waste Treatment Plants* refer to fires in sites where waste is temporarily stored while awaiting final treatment or disposal. *Landfill Fires*, refers to fires only in landfills which, as defined by Legislative Decree No. 36 of January 13, 2003, are areas designated for the disposal of waste through deposit on or in the ground, where waste is stored for over a year. This excludes sites used for short-term storage, under one year for disposal or under three years for recovery or treatment. A broader category includes *Fires at Mechanical Biological Treatment (MTB) Plants, Compactors, Recycling Centers, Collection Centers (CCRs), and Platforms* , encompassing facilities as well as incidents involving waste transport vehicles or dumpsters. MTB plants treat mixed waste through a mechanical phase, which separates inorganic materials for recycling, and a biological phase, which processes organic matter into biogas via anaerobic digestion or composting. *Fires in*

[7]”Parliamentary Committee of Inquiry into Illegal Activities Connected to the Waste Cycle and Related Environmental Offenses” n° 14 approved by the Committee August the 4th 2021.

Composting Plants are fires in the facilities that handle the organic fraction of urban or mechanically separated waste, converting it into compost. *Fires in Incinerators* are fires concerning industrial plants that burn waste to produce thermal or electrical energy. *Fires in Illegal Sites* involve unauthorized sites used for waste collection or storage. Finally, the category *Fires in Other Types of Facilities* captures incidents that do not fall into the aforementioned groups. Each record in the dataset includes details such as the fire's date and location and the facility type. Two additional categories, *STIR and SIR facilities* and *Sized Warehouses Full of Waste*, were excluded because they do not share the same function or purpose as the other categories under study. The first refers to waste shredding or packaging plants, where waste remains only briefly and is involved solely in pretreatment phase. SIR sites, by contrast, are contaminated areas rather than active facilities where waste is managed. Similarly, Seized Warehouses Full of Waste are already under the control of the competent authorities, as endangered ares. For this reason, any fire occurring at these sites could not be linked to increased operational pressure or to incidents related to illegal waste management. Including these categories would have compromised the consistency of the analyzed sample. The construction of these categories required a careful process of classification, ensuring that each fire was assigned to the most accurate type of facility. This organizational step was crucial in transforming a heterogeneous set of news-based events into a structured dataset that could be consistently analyzed.

In order to complete the dataset, additional data on fires in Italy were collected from the fire department intervention maps[8]. The maps include all different types of fires especially non waste related. Some examples are *Wildfires and Vegetation Fires* which includes any kind of forest fires, vegetated ares, hay bales or Mediterranean scrub, *Fires in Homes and Shops*, *Fires in Industrial Facilities*, *Fires in Agricultural Facilities* and *Vehicle Fires*, plus an additional category for all the fires that do not fall in any of the above. All these categories were included in a greater classification of *Non-Waste Fires* events which is not considered for the purposes of this study.

To this analysis purpose only the category *Fires in Waste Storage and Warehouses* is considered from the fire department dataset , which encompasses incidents occurring in warehouses, sheds, and silos where waste or various waste materials have caught fire. It also includes fires at businesses involved in the disposal of plastic or other types of waste. In merging these sources, substantial effort was dedicated to data cleaning and harmonization. Duplicates were removed, inconsistent entries were corrected, and irrelevant fire events were excluded so that only waste-related cases remained. Fires at waste treatment plants (309 cases) and illegal sites (257 cases) represent the most frequent categories, followed by incidents at other facilities such as landfills (82 cases) and waste storage sites or warehouses (97 cases). Less common but still significant are fires occurring at MBT plants, compactors, recycling centers, civic amenity sites, and waste platforms (112 cases), while fires in composting plants (13 cases) and incinerators (23 cases) are relatively rare. This distribution suggests that certain facility types are disproportionately affected by fire risks, likely due to differences in operational practices, safety standards, and regulatory compliance.

The overall trend in waste fires is presented in Figure 9. The graph indicates a marked increase in the number of incidents coinciding with the years in which the ban was announced and subsequently implemented. While the relatively low number of fires recorded in 2016 is primarily attributable to in-

[8]https://www.vigilfuoco.tv/mappe-interventi/ultimi-7gg.

Type of Waste Fire	Frequency
Fires at Other Types of Facilities	54
Fires in Illegal Sites	257
Fires in Incinerators	23
Fires in Composting Plants	13
Fires at MBT plants, compactors, recycling centers, civic amenity sites, and waste platforms	112
Fires at Waste Treatment Plants	309
Landfill Fires	82
Fires at Waste Storage Sites and Warehouses	97

Table 1: Number of recorded fire incidents by type of waste facility, indicating how frequently fires occur in different waste management and disposal contexts.

complete data, the sharp rise observed between 2017 and 2018 appears more substantial and meaningful. It is reasonable to advance the hypothesis that this surge was linked to China's import restrictions: following 2018, the number of fires begins to decline, initially at a slow pace, and more markedly right after. This trend may reflect a gradual adjustment within the waste management system, leading to a reduction in fire incidents over time. The aim of this research is to significantly associate the waste fires incidents increase to the proximity to waste treatment facilities and the disruption of China's waste trade partnership.

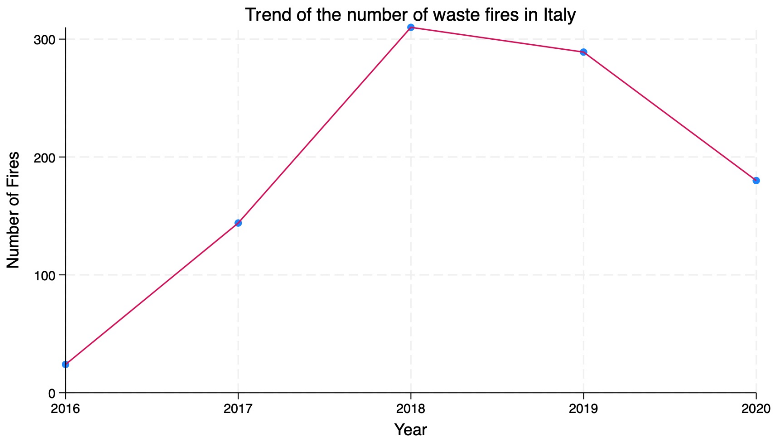

Figure 9: Number of waste fires from 2016 to 2020 in Italy.

Spatial patterns are shown in Figure 10, which highlights the geographical distribution of fires across Italian regions. The map reveals that waste fires are not localized phenomena but affect all major regions, suggesting that systemic factors drive the occurrence of these incidents, rather than isolated local issues.

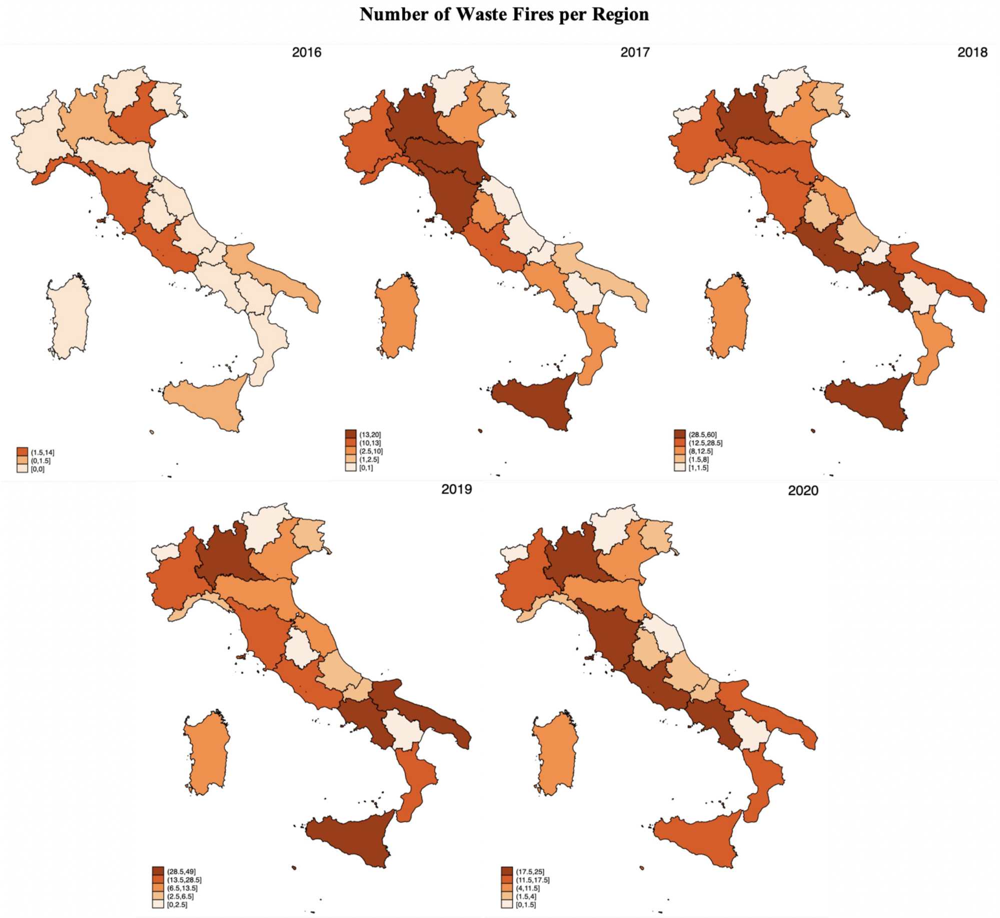

Figure 10: The distribution of the number of waste fires per region in each year (source: ISPRA).

Finally, the annual dynamics of waste fires relative to the number of facilities are summarized in Table 2. Between 2016 and 2018, the number of fires per facility rose sharply, peaking at 0.555 fires per facility in 2018. Afterward, the trend began to reverse, declining to 0.323 fires per facility by 2020. These results align with the temporal trend observed in Figure 9, reinforcing the hypothesis that the surge in 2017–2018 was driven by an external shocks, China's waste trade ban, and that the subsequent decline reflects an adaptation within the Italian waste management sector.

Year	Total Waste Fires	Number of Facilities	Fires per Facility
2016	24	581	0.041
2017	144	581	0.248
2018	310	559	0.555
2019	289	563	0.513
2020	180	557	0.323

Table 2: Distribution of the number of waste fires per waste facility in each year.

A deeper statistical description of the dependent variable used for the difference-in-difference analysis is provided in Table 3. The variable Number of Waste Fires has a mean of 0.333 but a median of 0, with over 81.6% of observations equal to zero. The extreme skewness (11.264) and very high kurtosis (193.659) confirm the presence of many zero values and a small number of extreme outliers (e.g., sites with as many as 27 fires). These characteristics justify the choice of a non-linear model—specifically a negative binomial regression, as discussed in the empirical section.

Percentiles	
1%	0
5%	0
10%	0
25%	0
50% (Median)	0
75%	0
90%	1
95%	2
99%	4
Descriptive Statistics	
Observations	2,841
Mean	0.333
Standard Deviation	1.213
Variance	1.472
Minimum	0
Maximum	27
Skewness	11.264
Kurtosis	193.659

Table 3: Descriptive statistics of the number of waste fires.

Table 4 provides further insight into the distribution of maximum annual fire counts per facility. Over half of the facilities (54.79%) experienced no fires in a given year, and approximately 27.69% experienced only one. The remaining cases show progressively smaller frequencies, with rare but extreme outliers of up to 27 fires. This confirms the heavy-tailed nature of the data.

Number of Fires	**Frequency**	**Percent**	**Cumulative %**
0	366	54.79	54.79
1	185	27.69	82.49
2	72	10.78	93.26
3	17	2.54	95.81
4	9	1.35	97.16
5	10	1.50	98.65
7	3	0.45	99.10
9	1	0.15	99.25
11	1	0.15	99.40
12	1	0.15	99.55
13	1	0.15	99.70
24	1	0.15	99.85
27	1	0.15	100.00
Total	**668**	**100.00**	–

Table 4: Distribution of the maximum annual number of fires observed per waste facility.

Taken together, these tables and figures present a consistent narrative: waste fire incidents are unevenly distributed across facility types and regions but are supposedly sensitive to broader systemic changes in their global chain. The statistical evidence will further underscore the heterogeneity of fire occurrences and the importance of using appropriate modeling techniques to account for the data.

4.2 Landfills and Waste Facilities

To study weather there is a correlation between the amount of waste treated by facilities and the number of waste fires in Italian municipalities and the effect if the China ban I collected data on municipal and special waste from the Italian Institute for Environmental Protection and Research (ISPRA) database. In particular, the data report information on the location and quantity of processed waste in the different types of waste facilities. From the municipal waste report[9] I reported data for eight types of facilities that treat municipal waste: *Waste Composting Plants*, *Integrated Anaerobic/Aerobic Waste Treatment Plants*, *Anaerobic Waste Digestion Facilities*, *Mechanical Biological Treatment (MTB)*, *Mechanical Treatment Facilities* and *Urban Waste Landfills*.

Municipal waste refers to a broad category of waste generated from households and similar sources. It includes both unsorted and separately collected household waste, such as paper, glass, metals, plastics, organic materials, textiles, wood, bulky items, waste electrical and electronic equipment (WEEE), batteries, and waste of a similar nature produced by other sources. Other forms of municipal waste include street-sweeping residues, waste from public spaces and shorelines, green waste from public areas, market cleaning waste, and certain types of cemetery-related waste.

The management of municipal waste is a shared responsibility among the state, regions, provinces, and municipalities. Municipalities play a critical role in ensuring efficient waste management, encompassing sanitary handling, organized collection, and a proper segregation of hazardous and cemetery waste. Effective systems focus on optimizing waste collection and weighing, particularly for primary packaging, while adhering to sustainable practices.

The waste management process involves several stages, from collection to final treatment, prioritizing material recovery and safe disposal. Material recovery integrates waste back into production cycles as substitutes for raw materials. Energy recovery, in contrast, converts waste into usable energy forms like heat or electricity. Separately collected waste undergoes pre-sorting before recycling in specialized facilities such as paper mills, glassworks, or plastic recycling plants. Organic waste is biologically treated through composting or anaerobic digestion, yielding compost for soil enrichment and biogas for energy use. These processes support soil fertility and combat degradation. Unsorted municipal waste is processed in mechanical or mechanical-biological treatment (MBT) plants. Here, recoverable materials like metals or high-calorific fractions are extracted for recycling or energy production. Residual waste is ultimately disposed of in landfills, ensuring minimal environmental impact. Through these measures, municipalities contribute significantly to sustainable waste management and resource conservation.

Regarding special waste facilities, data on location and treated waste quantities from ISPRA's spe-

[9]https://www.isprambiente.gov.it/it/pubblicazioni/rapporti

cial waste report[10] was collected. However, due to the lack of detailed information at the individual facility level, I limited the analysis to special waste landfills only. In fact, for all other types of special waste plants only regional data were available for the entire considered time period. While this limitation is acceptable for the purpose of this study, given the simplifications introduced later in the analysis, it significantly reduces the completeness of information concerning Italy's waste management infrastructure and disposal practices. This is particularly relevant considering that, in quantitative terms, special waste significantly exceeds municipal waste nationwide. Though, many waste treatment facilities manage both municipal and special waste, the quantities of treated waste is not the same. Special waste's landfills are divided in three different types: *Hazardous Waste Landfills*, *Non-Hazardous Waste Landfills* and *Inert Waste Landfills*. All type of waste implants considered in the dataset are displayed in Table 5.

Special waste encompasses all waste types that do not fall under the municipal category and originate from specific economic or productive activities. This includes waste generated by agricultural, agro-industrial, forestry, and fishing sectors, as outlined in Article 2135 of the Italian Civil Code. Additionally, materials from construction, demolition, and excavation activities are classified as special waste. Industrial and artisanal production processes, along with commercial and service sector activities, also contribute to special waste, provided the waste differs in nature or composition from domestic waste. Other examples include residues from waste recovery and disposal operations, sludge from water treatment, materials from flue gas treatment, and waste collected from septic systems. Healthcare facility waste, when not classified as municipal, falls under this category, as do end-of-life vehicles due to their specific regulatory and environmental considerations.

This classification ensures that special waste is managed through appropriate recovery, treatment, and disposal systems. By adhering to legal and environmental standards, efficient handling of these waste streams minimizes environmental impact while promoting sustainable practices.

The graph in Figure 11 illustrates how waste processing, measured in millions of tons, is divided between the different types of categories from 2016 to 2020. Non-Hazardous Waste Landfills consistently treated the largest volumes, followed by MBT Plants, while other facility types handled comparatively smaller amounts. The total waste treated peaked around 2018, with a slight decline observed by 2020. The continued dominance of Non-Hazardous Waste Landfills and MBT Plants underscores their critical role in large-scale waste processing and highlights their significance within the waste management infrastructure. The variable analyzed here is the total amount of waste treated by all types of plants. Its trend remains relatively stable over the years, likely because it reflects a combination of various effects, making it difficult to directly observe the impact of the import ban.

[10] https://www.isprambiente.gov.it/it/pubblicazioni/rapporti

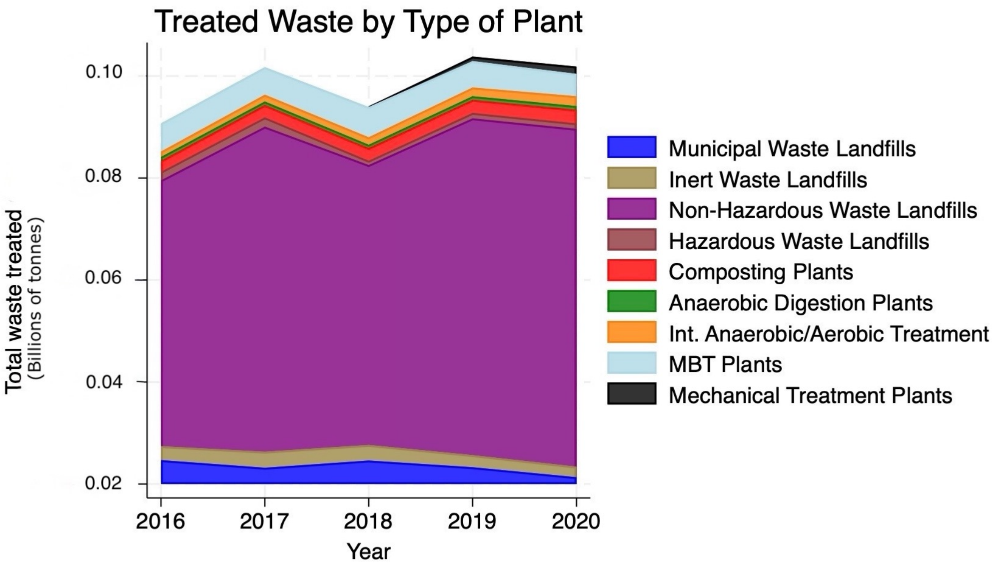

Figure 11: Stacked area graph on how treated waste are distributed among different types of plants and across time. Inert Waste Landfills, Non-Hazardous Waste Landfills and Hazarduous Waste Landfills treat only special wastes while the other categories are limited to the treatment of municipal waste. In the case of municipal waste, the graph's categories might not be mutually exclusive, and some treatment methods could represent different stages of the same waste stream's disposal (source: processed dataset from ISPRA).

Distribution of Waste Treatment Plant Types	Frequency
Anaerobic Digestion Plants (tonnes)	90
Composting Plants (tonnes)	872
Hazardous Waste Landfills (m^3)	40
Mechanical Treatment Plants (tonnes)	29
Inert Waste Landfills (m^3)	614
Integrated Anaerobic/Aerobic Treatment Plants (tonnes)	112
Mechanical-Biological Treatment Plants (tonnes)	307
Municipal Waste Landfills (m^3)	140
Non-Hazardous Waste Landfills (m^3)	637

Table 5: Frequency distribution of the different types of waste treatment plants in the dataset, expressed either in tonnes or cubic meters depending on the plant type.

The maps in Figure 12 show a snapshot of how the amount of waste treated, produced and exported is distributed in Italian regions. These data are regional from ISPRA and refer to year 2016, the data related to the rest of the years considered in the analysis are reported in the maps in appendix A. The data on treated and produced waste remain stable throughout the years, it is not possible to see notable variation only looking at regional data. It is also for this reason that this research looks at data per specific waste facility. The amount of waste exported by each region varies over time as it is clear in Figure 21 (in appendix A). However, the variation in per region exports does not show any sign of the China ban effect, likely because the data refer to total waste exports rather than disaggregated plastic waste exports, which were the primary category affected by the policy.

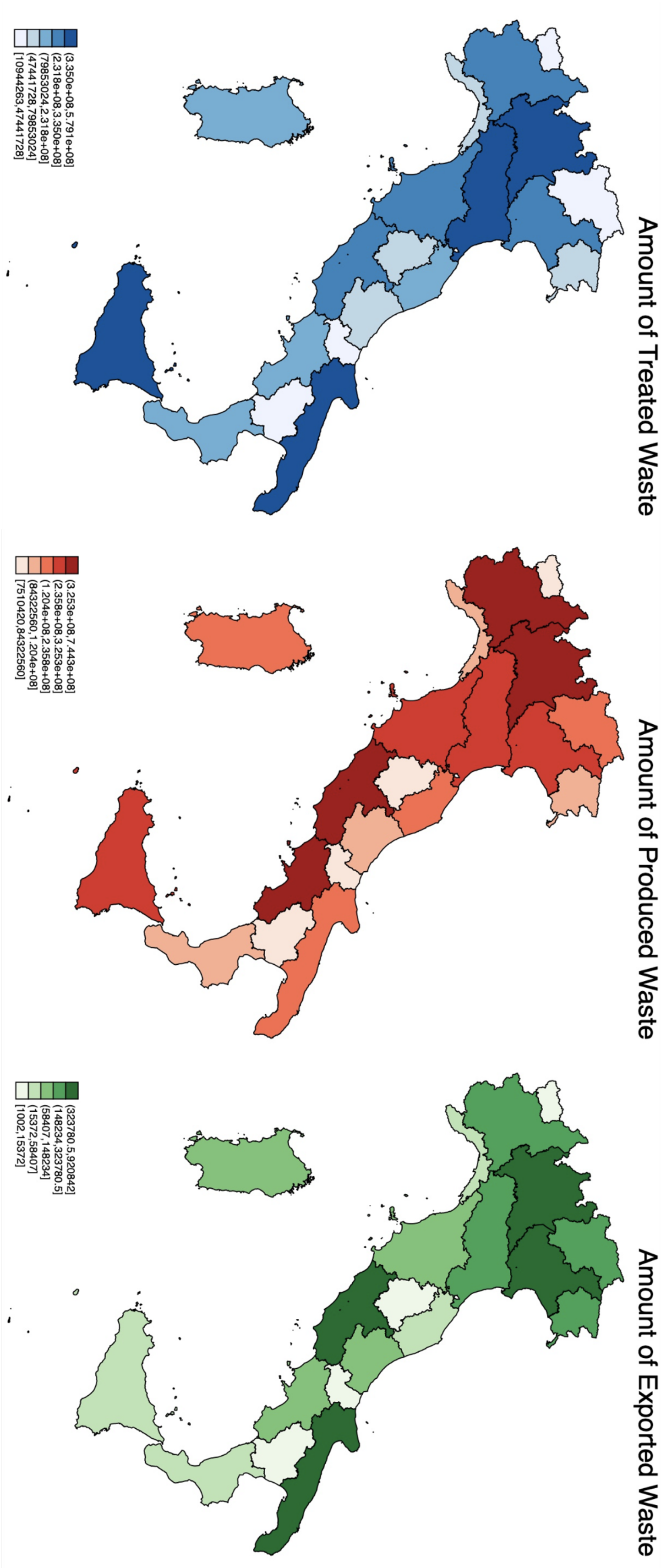

Figure 12: The amount of waste that was treated (map in blue), produced (map in red) and exported (map in green) in tonnes by each region in Italy in 2016 (source: ISPRA).

A deeper statistical description of the total amount of treated waste is provided in Table ??, which summarizes the annual volume of waste processed by each facility. The percentile values reveal a highly uneven distribution: while 50% of the facilities treat less than 20,322 tons annually, the top 1% handle more than 2,854,595 tons. The mean value of 173,276.5 tons is considerably higher than the median, indicating that the average is influenced by a small number of extremely large facilities. This pattern is confirmed by the very high standard deviation (543,096.5 tons), large variance (2.95×10^{11}), pronounced positive skewness (5.99), and high kurtosis (47.76), all of which signal a heavy-tailed distribution with numerous outliers.

Percentiles	
1%	7
5%	75
10%	293
25%	2,323
50% (Median)	20,322
75%	78,841
90%	346,601
95%	933,212
99%	2,854,595
Descriptive Statistics	
Mean	173,276.5
Standard Deviation	543,096.5
Variance	2.95×10^{11}
Skewness	5.99
Kurtosis	47.76

Table 6: Summary statistics of the total waste treated (in Tons) across all facilities and years.

Given these characteristics, a log transformation of the variable was applied to mitigate the effects of extreme values and produce a more symmetric distribution suitable for statistical modeling. Table 7 presents the summary statistics for the log-transformed total waste treated. After transformation, the distribution becomes far more balanced: skewness drops to -0.52 and kurtosis to 3.16, values much closer to those of a normal distribution. The percentiles also show a compressed range, with the median at 9.92 and the 99th percentile at 14.86, compared to the vastly larger range in the raw data.

Percentiles	
1%	1.95
5%	4.32
10%	5.68
25%	7.75
50% (Median)	9.92
75%	11.28
90%	12.76
95%	13.75
99%	14.86
Descriptive Statistics	
Mean	9.49
Standard Deviation	2.77
Variance	7.65
Skewness	-0.52
Kurtosis	3.16

Table 7: Summary statistics of the logarithm of total waste treated variable.

The improvement achieved through the log transformation is visually illustrated in Figure 13, which plots the density of the log-transformed variable. The figure clearly shows a smoother, bell-shaped curve, confirming that the extreme values in the original scale have been effectively moderated. This transformation not only stabilizes variance but also ensures that the modeling results are less sensitive to outliers, providing a more robust basis for subsequent econometric analyses.

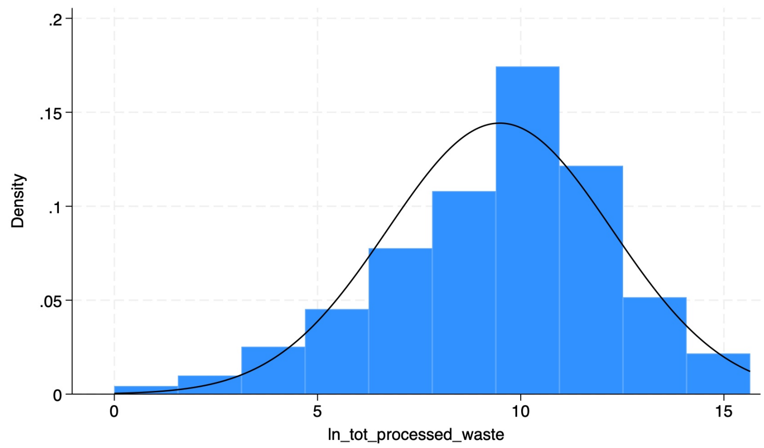

Figure 13: Distribution of the variable total treated waste in logarithm, on the x-axis and the density on the y-axis.

Finally, I collected data on waste production, export at a regional level that will be used as controls in the analysis. These data were obtained from the ISPRA database. The dataset contains 2,841 distinct waste treatment facilities, each located in a different municipality. In cases where multiple facilities were present within the same municipality, only the largest facility was considered for the analysis. This simplification had a small impact on the overall dataset, as such cases were relatively few. Moreover, this approach significantly facilitated the association between facilities and the nearest fire events, allowing a clearer attribution of each fire to a specific plant. Limiting the analysis to one facility per municipality does not affect the accuracy of the analysis, as waste management responsibilities and territorial impacts are typically governed at the municipal level. As such, the largest facility often represents the primary source of local waste activity and risk exposure, making it a reasonable proxy for environmental and operational assessments. This may not be true in the case of very big municipalities which, nevertheless, are a negligible number.

5 Empirical Analysis

This section presents the empirical strategy adopted to investigate the relationship between Italy's waste export dynamics, waste treatment capacity and waste-related fires. The analysis integrates multiple georeferenced and facility-level datasets to construct a comprehensive framework capable of capturing both spatial and sectoral dimensions of the waste value chain. The goal is to investigate how disruptions in the international waste trade, specifically the 2018 China waste import ban, affect domestic waste treatment capacity and the incidence of waste-related fires. By combining count-data, and difference-in-differences (DiD) methodologies, the study provides a comprehensive assessment of both temporal and spatial dimensions of Italy's waste value chain.

The empirical analysis is organized in the following way. Firstly, I adopt a difference in difference approach to assess the causal impact of China's import ban on fire incidents at a waste facility level. This model evaluates how the relationship between landfill capacity and waste-related fires changed before and after the China ban. By comparing treated and control groups over time, the DiD approach isolates the causal effect of the ban on the incidence of fires, while accounting for underlying trends unrelated to the policy shock. In the Results section I go more in detail on the pressure level of Italian waste facilities, before and after the import ban. Rather than only look at the results of the DiD I also observe the temporal dynamics of treated waste with visual representation. Finally, to gain deeper insights into the specific dynamics at play, particular attention is devoted to examining how the volume of treated waste influences the intensity of fire incidents at the facility level. This analysis is conducted using a negative binomial count model.

The structure provides greater possibilities to investigate and entangle the problem: rather than relying on a single equation to capture a potentially complex chain of effects, it enables a more targeted assessment of where the policy may be having an impact. This improves the chances of detecting significant relationships, even if the effect is concentrated in just one of the stages.

Together, these methods provide complementary perspectives. They improve the chances of detecting significant relationships, even if the effect is concentrated in just one of the analyzed elements. The DiD framework tests for structural breaks in this relationship around a major exogenous event. This multi-method strategy strengthens the empirical rigor of the study and offers robust insights into the complex interactions between global waste flows, local treatment infrastructure, and environmental risks.

5.1 Difference-in-Difference Approach

To quantify the impact of China's imports ban on fire incidents at waste facilities I use a difference in differences approach. This exploits both temporal variation before and after the policy, as well as cross-sectional differences in exposure to the ban. The use of a difference-in-differences framework is particularly appropriate for this context, as it is a well-established and widely used method for causal inference in policy evaluation. By comparing the change in outcomes between treated and control groups over time, DiD allows us to isolate the effect of the waste ban from broader temporal trends that could otherwise confound the analysis. This makes it a robust choice for assessing policy impacts in real-world settings where randomized experiments are infeasible. The variable measuring the amount of treated waste, the total volume of waste processed, is a continuous variable. Facilities are categorized according to their pre-ban waste flows: plants with higher volumes of treated waste are considered the treated group, under the assumption that these facilities were more directly affected by the sudden disruption of international waste markets. Plants with lower waste flows serve as a control group, providing a reference for changes in fire incidence unrelated to the ban. The specification includes an interaction between a post-ban indicator and a measure for treatment intensity. The aim is to estimate whether the interruption of a key international supply chain had a measurable effect on waste over accumulation in waste facilities and, consequently on the incidence of fires at waste facilities.

The dependent variable is the count of fire incidents, for which a negative binomial specification is retained to accommodate the overdispersed nature of the data. The main explanatory variables include: (i) a post-ban indicator capturing temporal variation, (ii) a continuous measure of treatment intensity based on the total volume of waste processed, and (iii) their interaction term, which isolates the differential change in fire incidents for highly exposed facilities after the policy shock. This interaction captures whether facilities with larger waste flows experienced a disproportionate increase in fire incidents following the interruption of the international supply chain. Specifically, the regression is as follows :

$$\log\left(\mathbb{E}(\text{Fires Num}_{it})\right) = \beta_0 + \beta_1 \cdot \log(\text{Tot Treated Waste}_{it}) + \beta_2 \cdot \text{Post} + \gamma \cdot X_{it} + \lambda_t + u_i. \quad (1)$$

Using the negative binomial framework, which will be analyzed more specifically later in the analysis, the model accounts for unobserved heterogeneity and excess variance in the fire count data, ensuring consistent and efficient estimation. Furthermore, employing a negative binomial specification with random effects adds rigor by explicitly accounting for overdispersion and unobserved heterogeneity across facilities, which are common challenges in count data on incidents like fires. Regional-level controls, such as waste export ratios, overall waste production, and population density, are also included to absorb confounding influences and improve identification. The term u_i captures unobserved heterogeneity at facility level and is introduced as a random effect. The control variables are included in X_{it}, while λ_t represents the time fixed effects.

However, this methodological approach faced important limitations. Most notably, detailed and disaggregated data on the treatment of plastic waste are not available at facility or municipal level.

For this reason, the analysis was necessarily based on the total amount of waste processed, which includes all waste categories and not only plastics. The total waste figures may not accurately reflect the specific pressure caused by the accumulation of non-exportable plastic waste, which was the main concern following the ban. The lack of specificity introduces substantial measurement noise into the estimation. Due to the too high level of aggregation of the key variable, facilities primarily dealing with non-plastic waste may be erroneously classified as treated, even if they experienced little to no impact from the policy change. As a result, the post × treatment interaction term risks conflating heterogeneous treatment intensities and incorrectly attributing effects, leading to downward bias in the estimated coefficients and reducing the model's ability to detect meaningful policy impacts.

The same issue has already emerged in the preliminary national-level analysis of export trends: while exports of plastic waste show a sharp and direct response to the Chinese ban, total waste exports appear merely partially affected and are therefore less informative in capturing the impact of the policy shock. A similar limitation applies to regional data on waste exports, which, being available only for total waste, cannot reflect the specific dynamics and pressures associated with plastic waste flows.

Moreover, the treatment variable of the DiD, total treated waste, is a continuous variable which introduces a series of non-trivial identification and estimation challenges (see Callaway et al. (2021)).

Due to this data limitation, the risk that estimated effects are confounded by unrelated variations of other waste streams weakens the identification strategy and makes it difficult to isolate a clear causal impact of the ban on fire incidents. For this reason, the results yield weak statistical significance, both for the interaction term and overall, due to the potential model misspecification. Nonetheless, the results from this preliminary analysis are reported in the next section, as they may still offer useful insights and serve as a basis for future research, particularly if more granular data on plastic waste becomes available.

Nevertheless, the analysis remains valuable: even noisy estimates in this setting provide suggestive results that facilities under greater waste pressure saw relatively higher fire incidence after the ban. Importantly, these findings offer a structured, data-driven basis for future work, highlighting the need for more granular measures of plastic waste treatment and for exploring heterogeneous effects across facility types. By transparently applying a widely recognized empirical strategy, this analysis anchors the broader discussion of waste management risks in a rigorous quantitative framework.

5.2 Treated Waste and Waste Fires

Following the difference-in-difference's results, which suggested an underlying positive association between waste pressures and fire incidents, it is important to further examine the mechanisms at play. To gain a more nuanced understanding, the analysis now shifts focus from policy timing to the intensity of waste treatment itself.

The aim of this step is to examine whether facilities processing larger volumes of waste are systematically more prone to fire incidents, independent of the specific timing of China's import ban. Understanding this relationship is crucial for two reasons: first, it sheds light on the operational vulnerabilities of waste management infrastructure under high load conditions, identifying a particular sensitivity to a supply chain disruption; second, it offers practical insights for risk mitigation and regulatory oversight, regardless of external policy shocks.

The dependent variable, which represents a count of fire incidents per facility per year exhibits a high concentration of zeros. 81% of the observations report zero fires, and 51% of the facilities did not experience any incident throughout the entire observation period, which are considered structural zeros.

In such a context, an analysis is carried out to study the frequency of fires occurring in waste treatment facilities. Using a standard count model, in particular the negative binomial, which assumes that all zero and positive outcomes are generated by a single stochastic process and that each observation has a positive probability of experiencing an event. In the single estimation using the standard count model, the expected frequency of the fire events is estimated using a left-truncated negative binomial with random effects, in order to account for unobserved heterogeneity across facilities.

A correlation analysis, presented in Table ??, supports the use of a nonlinear count data model, already partially discussed in the dataset analysis. While the Pearson correlation between the number of fires and total waste treated is weak and statistically insignificant, both Spearman's rho (0.1813, $p > 0.01$) and Kendall's tau-b (0.1449, $p < 0.01$) indicate a statistically significant positive monotonic association. This suggests that the relationship is not linear and that standard linear regression would be inappropriate.

Method	Coefficient	p-value	Significance
Pearson (linear)	0.0526	–	Not significant
Spearman (rank-based)	0.1813	0.0000	Significant at 1%
Kendall's tau-b (ordinal)	0.1449	0.0000	Significant at 1%

Table 8: Correlation Between Number of Fires and Total Waste Treated

Additionally, this model is appropriate in this setting because the dependent variable is discrete and exhibits overdispersion, that is, the variance exceeds the mean. In fact, the count variable is believed to be generated by a Poisson-like process, except that the variation is allowed to be greater than that of a true Poisson. This extra variation is referred to as overdispersion. Moreover, it accounts for the excess of zeros in the dataset.

In its standard formulation, the Poisson regression model assumes that the dependent variable y_i follows a Poisson distribution with mean μ_i, such that:

$$y_i \sim \text{Poisson}(\mu_i),$$

where the mean μ_i is modeled as a log-linear function of the variables:

$$\mu_i = \exp(\mathbf{x}_i'\boldsymbol{\beta} + \text{offset}_i).$$

To account for the heterogeneity across observations, that is not captured by the included variables, the Poisson mean is assumed to be a random variable influenced by a gamma-distributed error term.

The term μ_i is replaced by μ_i^*. Specifically, it is assumed that:

$$y_i \sim \text{Poisson}(\mu_i^*), \quad \mu_i^* = \exp(\mathbf{x}_i'\boldsymbol{\beta} + \text{offset}_i + \zeta_i),$$

where the error term, in the well-known special case, satisfies:

$$e^{\zeta_i} \sim \text{Gamma}(1/\alpha, \alpha).$$

This structure leads to the marginal distribution of y_i being negative binomial, with variance given by:

$$\text{Var}(y_i) = \mathbb{E}\left[\text{Var}(y_{|}\mu_i^*)\right] + \text{Var}\left[\mathbb{E}(y_i \mid \mu_i^*)\right] = \mu_i^* + \text{Var}(\mu_i^*) = \mu_i(1 + \alpha\mu_i).$$

Here, α is known as the dispersion parameter. A larger value of α implies a greater degree of overdispersion. When $\alpha = 0$, the model simplifies to a Poisson regression model[11]. Empirically, the quadratic variance function is a versatile approximation in a wide variety of cases of overdispersion data.

The marginal distribution of y is a Poisson-gamma mixture with a closed form, the negative binomial distribution, whose probability mass function is :

$$\Pr(Y = y \mid \mu, \alpha) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(\alpha^{-1})\,\Gamma(y+1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\mu + \alpha^{-1}}\right)^{y},$$

where $\Gamma(\cdot)$ denotes the gamma integral that specializes to a factorial for an integer argument[12].

Due to the structure of the data tough, the model is panel. In particular, a random effect panel model where $y_{it} \mid \gamma_{it} \sim \text{Poisson}(\gamma_{it})$ and where $\gamma_{it} \mid \alpha_i \sim \text{Gamma}(\mu_{it}, \alpha_i)$. Here $\mu_{it} = \exp(x_{it}'\beta + \text{offeset}_{it})$. This yields the model:

$$\Pr(Y_{it} = y_{it} \mid \mathbf{x}_{it}, \alpha_i) = \frac{\Gamma(\mu_{it} + y_{it})}{\Gamma(\mu_{it})\Gamma(y_{it} + 1)} \left(\frac{1}{1 + \alpha_i}\right)^{\mu_{it}} \left(\frac{\alpha_i}{1 + \alpha_i}\right)^{y_{it}}.$$

For a random-effects overdispersion model, we allow α_i to vary randomly across groups; namely, we assume that $1/(1 + \alpha_i\ ) \sim \text{Beta}(r, s)$.

In the negative binomial model, the variance of the dependent variable is expressed as:

$$\text{Var}(Y_{it} \mid X_i) = \mu_i + \alpha\mu_i^2,$$

where, as mentioned, μ_i is the conditional mean and α the over-dispersion parameter. The additional term $\alpha\mu_i^2$ allows the variance to grow faster than the mean, making the model particularly suitable for over-dispersive count data, such as fire incidents, which are unlikely to be evenly distributed across facilities or regions. The estimated coefficients β are interpreted on the log scale:

$$\frac{\partial \log(\mu_i)}{\partial(X_{it})} = \beta_t.$$

[11] Cameron and Trivedi (2013)
[12] Cameron and Trivedi (2010)

Exponentiating these coefficients, $\exp(\beta_t)$, yields the incidence rate ratio, which represents the multiplicative change in the expected number of incidents associated with a one-unit increase in X_t, holding all other factors constant.

Specifically, the regression is as follows.

$$\log\left(\mathbb{E}(\text{Fires Num}_{it})\right) = \beta_0 + \beta_1 \cdot \log(\text{Tot Treated Waste}_{it}) + \gamma \cdot X_{it} + \lambda_t + u_i. \tag{2}$$

The negative binomial regression uses a logarithmic link function to model the expected count of fire incidents, the dependent variable. This log transformation ensures that the predicted counts are always positive and addresses overdispersion. The term u_i captures unobserved heterogeneity at facility level and is introduced as a random effect to account for time-invariant characteristics that may influence the frequency of fire incidents. The control variables are included in X_{it}, while λ_t represents the time fixed effects.

6 Results

6.1 Difference-in-Difference

The DiD results presented in this sub section are insightful even tough they present limitations. The lack of specificity of the processed waste data introduces substantial measurement noise into the estimation. The model considers as treated the group of plants that had higher flows of treated waste during the observed year, and can be considered to be more affected by the ban. Still, due to the too high level of aggregation of the key variable, facilities primarily dealing with non-plastic waste may be erroneously classified as treated, even if they experienced little to no impact from the policy change. As a result, the post × treatment interaction term risks blurring heterogeneous treatment intensities and incorrectly attributing effects, leading to downward bias in the estimated coefficients and reducing the model's ability to detect meaningful policy impacts.

Additionally, as pre-treatment data is considered only 2016 which may be a too small basis to have significant estimates of the effect. In the estimation the year of the announcement of the ban, 2017, is excluded from the regression. The intuition is that there is a high probability that the fire phenomenon increases since the announcement of the ban, for this reason it would be biased to consider 2017 as pre if we are measuring the effect on the number of fires.

Moreover, it is worth mentioning that there are some additional interpretational problems when considering a continuous treatment variable as explained in Callaway et al. (2021). A binary DiD framework, assuming parallel trends in the absence of treatment allows for clean identification of the average treatment effect on the treated. However, with a continuous treatment, comparing units that receive different levels of the treatment introduces an additional layer of complexity. This includes the possibility of selection bias, since those receiving higher doses may systematically differ from those with lower amounts in unobservable ways. Moreover, identifying marginal causal effects, such as the average response to a change in treatment, requires stronger assumptions, stronger parallel trends across all treatment levels. This means assuming that units would have followed the same outcome path regardless of how much treatment they received, which is often implausible in practice. To address these issues, an alternative way could be to use non parametric DiD methods, in order to obtain more interpretable causal quantities and to allow for flexible treatment effect heterogeneity. Though this is not the case in the analysis. Nevertheless, adopting a continuous treatment approach allows for a more nuanced analysis that can capture varying intensities of exposure to the ban, offering richer insights than a simple treated-versus-control comparison.

In the following Table 9 are reported the results of the difference in difference analysis. The estimated results, within the framework, provide limited evidence of a causal effect of the intervention on the number of fire incidents. The key DiD, the interaction coefficient, capturing the differential post-treatment change for the treated group, is positive but not statistically significant, suggesting that the intervention did not lead to a significant measurable increase in fire incidents relative to the control group. Similarly, the post-treatment dummy is also insignificant, indicating no general time trend affecting both groups. However, these variable are positive which, considering the limitations of the data and the complexity of the reality, is still a worth mentioning result. This is confirmed by the marginal effects, reported in the second column of the table. On the other hand, several control variables are significantly associated with the outcome: isolation has a positive and significant effect. The marginal effects suggest that a one-unit increase in the isolation index is associated with approximately one additional fire incident. The ratio export variable is strongly negatively associated with fire incidents, indicating that a higher share of waste being exported correlates with fewer incidents. Additionally, population is positively associated with fire occurrences.

The overdispersion parameter, r, is estimated at 5.22, $\ln r = 1.654$. This suggests that the variance in the number of fire incidents exceeds the mean, justifying the use of a negative binomial model over a Poisson model for these data. Additionally, the estimated standard deviation of the random effects, s, equals 0.784, $\ln s = 1.86$, highlighting significant variability across plants not explained by the observed variables. The unobserved heterogeneity justifies the inclusion of random effects in the model. These specifications strengthen the credibility of the estimates by ensuring that plant-level differences not captured by observed covariates do not bias the results.

The statistical tests further support the robustness and appropriateness of the model specification. The Wald chi-squared test for joint significance yields a value of 197.74 ($p < 0.001$), indicating that the model as a whole is statistically significant. Moreover, the likelihood ratio test comparing the random-effects model to a pooled negative binomial model ($\chi^2 = 214.70$, $p < 0.001$) strongly rejects the null hypothesis that the variance of the random effects is zero. This confirms that unobserved heterogeneity across groups plays a significant role and justifies the use of the random-effects specification over a pooled model. It is possible to asses that the validity of the model is strong and suggests that the inclusion of facility-level random effects captures important unobserved variation in the incidence of fires.

Table 9: Difference-in-Differences Negative Binomial Regression and the Marginal Effects

	(1) DiD Estimates	(2) Marginal Effects
Fires Number		
Ln(Total Waste Treated)	0.0990	0.0990
	(0.094)	(0.094)
Post	1.278	1.278
	(1.011)	(1.011)
Interaction DiD	0.0595	0.0595
	(0.095)	(0.095)
Isolation	1.022^{***}	1.022^{***}
	(0.368)	(0.368)
Ratio Export	-17.04^{***}	-17.04^{***}
	(5.445)	(5.445)
Ln(Population)	0.341^{***}	0.341^{***}
	(0.086)	(0.086)
Year = 2016	0	0
	(.)	(.)
Year = 2018	0.470^{***}	–
	(4.07)	
Year = 2019	0.474^{***}	–
	(4.19)	
Year = 2020	0	–
	(.)	
Constant	-7.692^{***}	–
	(−4.69)	
ln_r	1.654^{***}	–
	(9.19)	
ln_s	-0.243^{*}	–
	(−1.66)	
Observations	2260	2260

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Having discussed the results of the DiD, which provided only limited statistical evidence of a causal effect but nonetheless indicated a positive association between the policy change and fire incidents, it is useful to complement those findings with a closer look at the underlying waste flows themselves. While the DiD framework controls for confounding factors and unobserved heterogeneity, it may obscure the raw temporal patterns that drive the observed effects. By focusing directly on the amount of treated waste before and after the import ban, we can better understand the operational pressure on Italian facilities that likely underpins the positive, even if statistically weak, interaction term from the DiD analysis. This descriptive perspective helps contextualize the DiD results and supports the interpretation that the policy shift did exert upward pressure on domestic treatment volumes, even if alternative trade routes and data aggregation limit the precision of the estimates.

Looking only at the the amount of treated waste in each plant before and after the import ban, the effect of the China ban on the pressure of Italian waste facilities is observed. Figures 14 and 15 provide a visual representation of the temporal dynamics of treated waste, with particular emphasis on 2018 as a pivotal year for comparison.

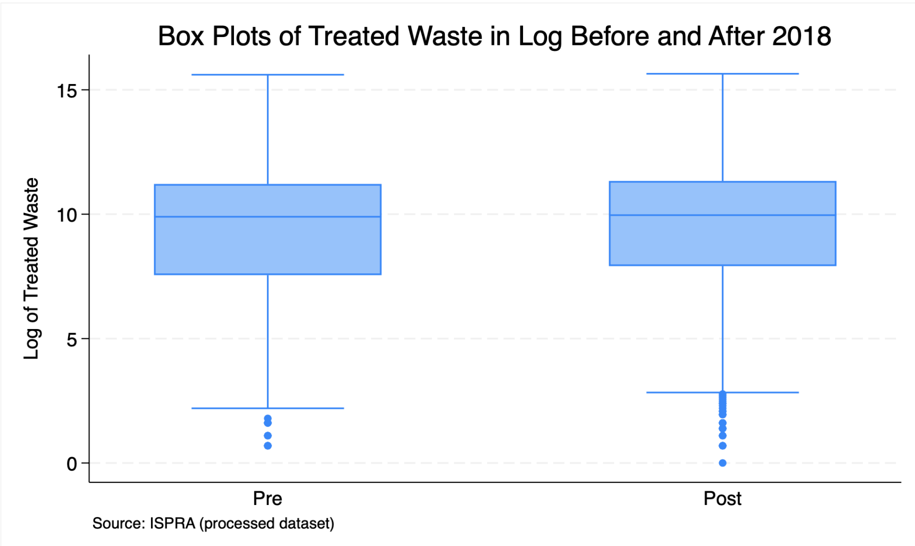

Figure 14: Distribution of the logarithm of treated waste volumes before and after the year 2018. The x-axis categorizes the data into two periods: "Pre" (before 2018) and "Post" (from 2018 on wards).

Figure 14 presents box plots illustrating the log-transformed treated waste before and after 2018, allowing for a visual assessment of any distributional shifts across the two periods. Likely due to the level of aggregation of the data, there is not an evident change unless Figure 15 is considered. The line graph shows the trend in logarithmic values of treated waste from 2016 to 2020. This reveals an increase in treated waste after 2017, with an upward shift between 2017 and 2019, followed by a stabilization from 2019 to 2020. The trajectory is consistent with the regulatory change influencing waste treatment volumes. The increase begins in 2017 when China started to reduce its plastic waste import volumes but the ban was formally put in place in January 2018. This specific year is considered as the threshold even because it divides more equally the two groups.

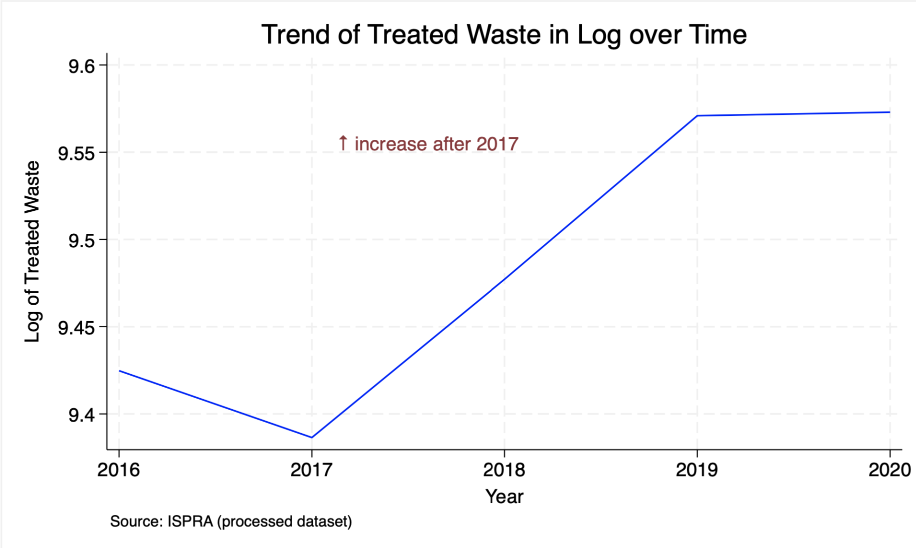

Figure 15: Logarithmic trend of treated waste from 2016 to 2020. The x-axis represents the years, while the y-axis denotes the logarithm of treated waste.

Period	Mean	Std. Dev.	Observations
Before 2018	9.406	2.801	1,162
After 2018	9.540	2.739	1,679

Table 10: Summary statistics of ln(Total Waste Treated) before and after 2018

Period	Mean	Std. Dev.	Observations
Before 2018	165649.3	516591.9	1,162
After 2018	178555.1	560797.9	1,679

Table 11: Summary statistics of Total Waste Treated before and after 2018

In order to provide a quantification of the observed change in the amount of treated waste post-2018, Table ?? and ?? present summary statistics for the log-transformed and raw data, respectively. In Table ??, the difference in mean logarithmic values before and after 2018 is 0.134, which corresponds approximately to a 13% increase in treated waste, assuming a log-linear relationship. Looking at the data in levels (Table ??) there is still evidence of this change.

While these patterns suggest a potential effect of the Chinese import ban, they remain descriptive. A more rigorous causal inference has been addressed in DiD analysis. It is observed a general increase in the pressure on Italian waste treatment facilities following the implementation of the Chinese import ban. However, no definite causal relationship can be determined, likely due to substantial noise in the data.

Additionally, another notable source of this noise is the emergence of alternative international waste trade routes in the aftermath of the Chinese ban, particularly the redirection of plastic waste exports toward countries such as Turkey. These new trade dynamics have absorbed part of the pressure that would otherwise have fallen entirely on domestic treatment systems, thereby diluting the observable effect in the data.

Nonetheless, it is important to note that the estimated coefficient remains positive, suggesting that the underlying relationship is in the expected direction. It is plausible to assume that, with access to a cleaner measure of total waste that isolates plastic waste, or under a counterfactual scenario where no alternative destinations like Turkey had absorbed part of the flow, the estimated effect would be both larger in magnitude and statistically significant.

6.2 The Effect on Waste Fires

As the analysis progresses, this subsection analyses the results of the impact on the number of waste fires in Italy. The estimates of the negative binomial model are reported in Table 12. This approach assumes that the possibility of having either a zero or a positive outcome is generated by a single stochastic process and that each observation has a positive probability of experiencing an event.

The results of the random effect negative binomial regression model offer insightful evidence on the determinants of the number of fires across different waste plants over time. The model's Wald chi-square test ($\chi^2(8) = 217.06$, $p < 0.001$) confirms the joint significance of all the variables. In particular, the dependent variable, the logarithm of the total amount of treated waste is positively and significantly associated with the incidence of fires. The effect is small but statistically significant, indicating that a 1% increase in treated waste is associated with approximately a 0.145% increase in the expected count of fires.

Additionally, the variable isolation also shows a positive and significant effect, suggesting that more isolated facilities are at higher risk. On the contrary, the ratio export variable shows a strong negative association with fire counts. As it was imaginable, a greater proportion of waste exported is associated with reduced fire incidents domestically. Also, the logarithm of the population is a significant positive predictor, reflecting increased fire risks in more densely populated or urbanized areas. Year fixed effects indicate that, relative to the baseline year (2016), the incidence of fires significantly increased in all subsequent years, with the greater jump in 2018 and 2019.

In the context of negative binomial regression, r captures the overdispersion of the model, that is, the extent to which the variance exceeds the mean, as opposed to the Poisson model. The estimated value of $\ln r = 1.67$ which corresponds to $r \sim 5.33$ and indicates substantial overdispersion, justifying the use of the negative binomial. Overall, the significant random-effects component, shown by the likelihood ratio test comparing the random-effects model to a pooled negative binomial model ($\chi^2(01) = 249.98$, $p < 0.001$), justifies the use of a random-effects specification, highlighting the importance of accounting for unobserved heterogeneity across plants. The estimated value of $\ln s = -0.07$ corresponds to a standard deviation of approximately 0.93 for the random effects, indicating substantial variability across plants that is not explained by the included variables, thus additionally justifying the use of a random effects model.

In order to provide a more interpretable account of the estimated associations, average marginal effects were computed following the random-effects negative binomial regression and are reported in the second column in Table 12. The average marginal effects are computed as a weighted average of the individual marginal effect for each observation. In fact, for non linear models, average behavior of individual observations differs from the behavior of the average individual.

While the raw model coefficients express changes in the log of the expected number of fire incidents per unit change in each explanatory variable, the marginal effects translate these relationships into changes in the expected count of fires, offering a more intuitive interpretation. The results reveal that a 1% increase in the total amount of waste treated is associated with an average increase of 0.045 fires, holding other factors constant. Facilities that are geographically isolated are expected to experience 0.285 more fires on average than their non-isolated counterparts. The proportion of waste exported shows a strong and statistically significant negative association with fire incidence of one-unit increase per an average reduction of approximately 5.76 fires. This result supports the interpretation that reliance on export channels influences fire risks. An increase in population size is positively associated with fire incidence, with a 1% rise in population leading to an estimated 0.10 additional fires. Again, year dummies further indicate the statistically significant increase in fire incidents for all years between 2017 and 2020, with the largest average increases observed in 2018 and 2019 of approximately 0.43 additional fires each. These results substantiate and contextualize the initial regression results, confirming both the direction and significance of effects.

Evidence of the relevance of the supply chain shock caused by China's waste import ban, and its serious environmental consequences, emerges throughout the entire analysis. While the total amount of processed waste explains only a modest share of fire incidents, partly due to the high level of aggregation of the variable, which introduces measurement noise, the effects is reiterated when considering the ratio export and the year fixed effects. The export variable shows the strongest and most significant association: facilities located in regions with higher export ratios tend to experience substantially fewer fires. Importantly, this variable is measured at only the regional level and refers to total waste exports. It is not specifically related to plastics nor at the facility level making the strength of the observed effect all the more notable.

Naturally, this chain of indirect mechanisms limits the ability to identify a direct causal effect. Nonetheless, the year effects reinforce the interpretation: fire incidents increase sharply in the years immediately following the Chinese import restrictions, aligning with the timeline of the ban. Taken together, the year dummies reflect the timing of the policy shock, the export ratio captures its operational consequences, and the total amount of waste processed at the facility level indicates the contribution of treatment volume to fire risk. These results, while correlational, point to a coherent and concerning pattern linking international policy shocks to local environmental hazards.

Table 12: Negative Binomial Regression and Marginal Effects

	(1) Log Incidence Rate Ratio	(2) Marginal Effects
Fires Number		
Ln(Total Waste Treated)	0.145^{***}	0.045^{***}
	(0.025)	(0.009)
Isolation	0.916^{***}	0.285^{***}
	(0.330)	(0.105)
Ratio Export	-18.54^{***}	-5.763^{***}
	(5.000)	(1.638)
Ln(Population)	0.321^{***}	$.099^{***}$
	(0.078)	(0.029)
Year = 2016	0	0
	(.)	(.)
Year = 2017	1.733^{***}	0.211^{***}
	(0.242)	(0.029)
Year = 2018	2.350^{***}	0.429^{***}
	(0.236)	(0.044)
Year = 2019	2.355^{***}	0.432^{***}
	(0.235)	(0.043)
Year = 2020	1.887^{***}	0.254^{***}
	(0.241)	(0.032)
Constant	-7.958^{***}	–
	(1.216)	
/		
ln_r	1.673^{***}	–
	(0.157)	
ln_s	-0.0720	–
	(0.138)	
Observations	2841	2841

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 The Level of Particulate Matter

Several features of wildfire smoke make it a valuable natural experiment to study the effects of air quality on labor market outcomes. Wildfire smoke events occur regularly and their presence in the Italian press has increased due to the growing relevance of the phenomenon. This is not uniquely related to waste fires, though the evidence analyzed in this research can be considered part of the broader set of fire-related occurrences. Of course, the aim of this thesis has been, partially, already achieved in the empirical analysis and the results section, evaluating the effect of the China ban on Italian waste management facilities. A further step, that here is only outlined concerns the potential role of increasing waste fires in aggravating air pollution levels. Air pollution, in turn, generates consequences that extend well beyond health, with implications for economic activity and social well-being. As a final direction for future research, I examine recent trend of particulate matter concentrations by source sector to better understand the evolution.

Drifting wildfire smoke plumes create sharp air pollution shocks. The recent study by Borgschulte et al. (2022) shows that at the daily level, an additional day of wildfire smoke increases concentrations of ground-level fine particulate matter (PM2.5) by an average of 2.2 μg/m3, about one-third of the daily standard deviation. The same research shows that an additional day of smoke raises a county's quarterly average PM2.5 concentration by about 0.06 μg/m3. By controlling flexibly for wind direction, they find that these estimates remain largely unaffected, indicating that fire smoke rather than other pollution sources upwind are responsible for the variation in air quality.

Ambient air pollution consists of both gaseous pollutants, such as tropospheric ozone (O3), nitrogen dioxide (NO2), volatile organic compounds (VOCs), carbon monoxide (CO), and sulfur dioxide (SO2), and particulate matter (PM) fractions, including PM10 and PM2.5. Among these, PM2.5 represents the greatest threat to human health due to its ability to penetrate deep into the respiratory system (WHO, 2016). In several regions, large quantities of PM2.5 originate from landscape fires, many of which are deliberately ignited for agricultural or land management purposes, such as forest clearing or post-harvest residue burning (Reddington et al., 2015; Zhang et al., 2017; Cusworth et al., 2018).

Wildfires and managed burns, which supposedly can include illegal and abusive waste fires, contribute significantly to PM2.5 emissions, often affecting air quality across vast geographic areas. Particulate matter, particularly PM2.5 and PM10, serves as a primary metric to assess air pollution caused by fires. These particles are direct by-products of biomass combustion and are emitted in large quantities during fire events. PM2.5 which considers particles with a diameter of 2.5 micrometers or smaller, is especially significant due to its ability to penetrate deep into the lungs and enter the circulatory system, making it a critical indicator of health-related impacts. PM10, which includes fine and coarse particles (up to 10 micrometers in diameter), captures a broader range of emissions. The widespread use of PM2.5 and PM10 in fire monitoring is due to their strong correlation with combustion intensity, their persistence in the atmosphere, and their established links to adverse respiratory and cardiovascular outcomes. As such, they offer a reliable proxy for evaluating both the spatial extent and health burden of fire-related air pollution.

Using data from ISPRA I look at the level of PM2.5 emissions in Italy across time. Overall, total

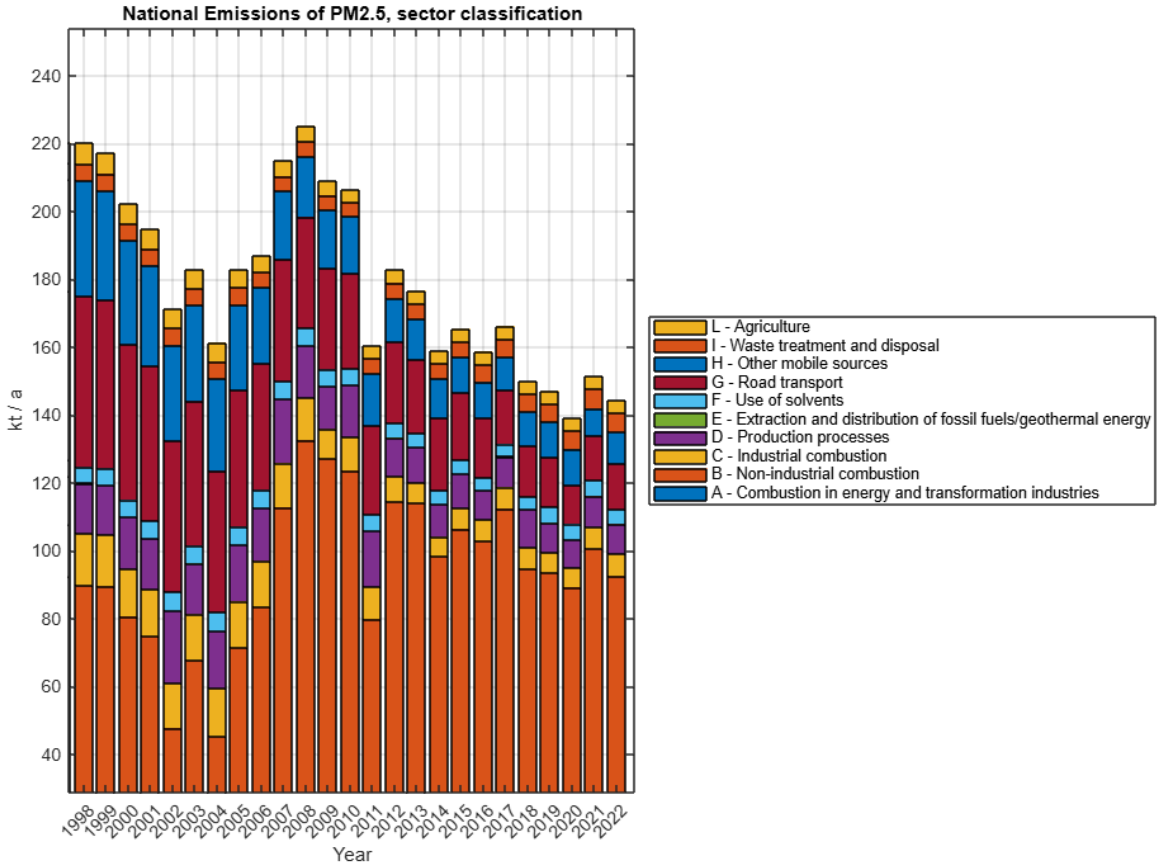

Figure 16: Italy's trend of PM2.5 emissions divided per each production sector. The contribution of non-industrial combustion stands out as the most significant and persistent source. This includes small scale, combustion activities including wildfires and waste fires. The category of Waste treatment and disposal only includes the combustion of waste in incinerators or co-incinerators (source: processed dataset from ISPRA).

emissions show a marked decline over the years, with a reduction of approximately 39%. The road transport sector, which accounted for 9.3% of total PM2.5 emissions in 2022, experienced a substantial decrease of 75% over the entire period. Conversely, emissions from non-industrial combustion increased by nearly 38% in the same timeframe, becoming the dominant source in 2022 with a contribution of 63.8% to total emissions. This is the sectors that includes wildfires as well as waste fires. Emissions from waste treatment and disposal do not consider illegal or abusive combustion of waste or accidental fires in waste facilities but only the combustion of waste as waste management activity. The level of this type of emission remain stable and low across time. Emissions from non industrial combustion remain the predominant form of PM2.5 emission in the atmosphere in Italy and the fire phenomenon cannot be overlooked.

The chart in Figure 17 illustrates the national emissions of PM10 by sector from 1990 to 2022. A clear overall decreasing trend is evident, with total emissions declining from over 400 kt/year in the early 1990s to less than 200 kt/year in recent years. This reduction reflects the effectiveness of technological improvements, stricter regulations, and structural changes in several sectors, particularly energy production and industrial combustion.

Despite this general decline, the contribution of non-industrial combustion stands out as the most significant and persistent source across the entire period. While emissions from sectors such as combustion in energy and transformation industries (A) and industrial combustion (C) have markedly decreased, non-industrial combustion has maintained a dominant share. This finding underlines the particular challenge posed by small-scale, diffuse combustion activities, which are harder to regulate and monitor compared to large industrial sources.

Other sectors, such as production processes (D) and other mobile sources (H), also contribute considerably, although their relative importance has diminished over time. Interestingly, fluctuations can be observed around 2005–2010, with temporary increases in emissions, suggesting the influence of sector-specific or external factors such as economic activity or regulatory delays.

Although the downward trajectory in total PM10 emissions is a positive outcome, the problem cannot be considered resolved. The persistent weight of non-industrial combustion in particular calls for continued policy attention. Moreover, beyond the categories explicitly reported, the issue of open burning, as for illegal waste fires, remains a pressing concern. These events, often unrecorded in official inventories, contribute significantly to local PM10 peaks and release a complex mixture of toxic pollutants.

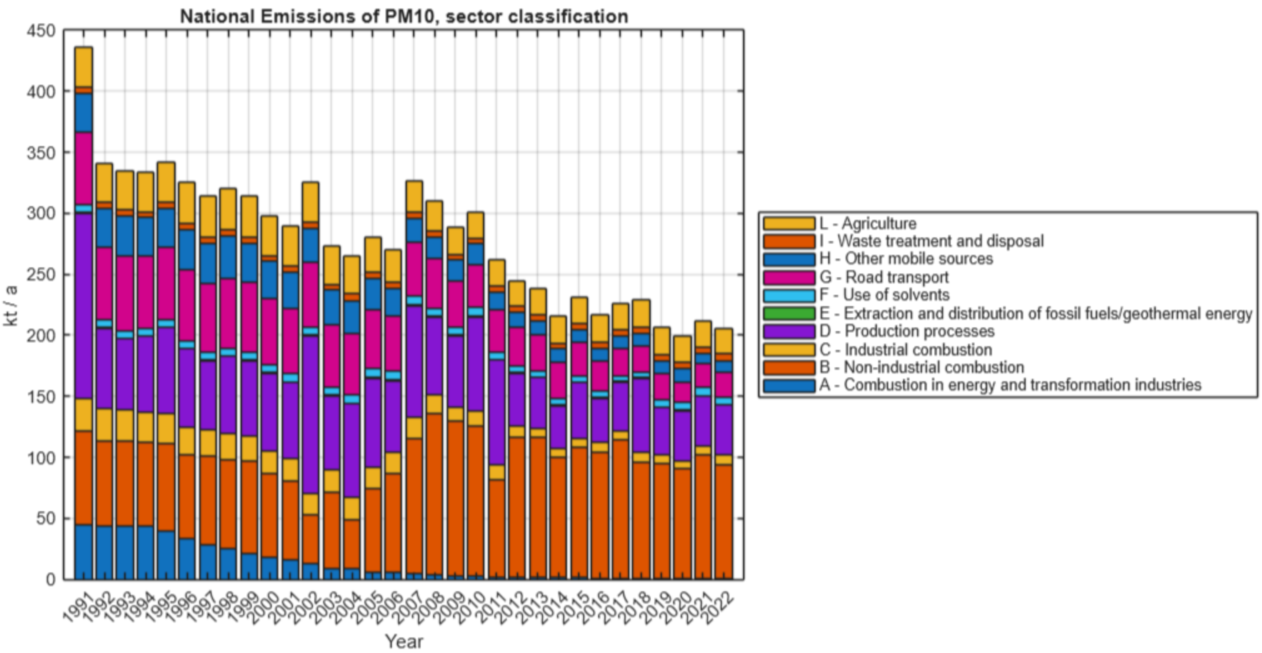

Figure 17: Italy's trend of PM10 emissions. The contribution of non-industrial combustion stands out as the most significant and persistent source. This includes small scale, combustion activities including wildfires and waste fires. The category of Waste treatment and disposal only includes the combustion of waste in incinerators or co-incinerators (source: processed dataset from ISPRA).

Finally, the temporal dynamics of PM emissions from fire events are characterized by both acute spikes and longer-term chronic contributions. During active burning phases particulate concentrations can reach extreme levels; for example, wildfire plumes frequently elevate PM2.5 above 200–300 $\mu g/\mathrm{m}^3$ over downwind communities, values that far exceed daily air quality guidelines. In contrast, recurrent fire activity across seasons contributes to sustained background elevations of particulate matter, often prolonging exposure well beyond the immediate fire event. This chronic exposure results in cumulative health impacts, as well as more definite economic negative effects. The dual nature of fire-related particulate pollution—episodic peaks superimposed on seasonal or annual background loads—underscores the importance of monitoring both PM2.5 and PM10 as critical indicators of the burden of wildfires on air quality and public health. Even tough the national level of emission has been decreasing in the last 20 years the problem remain and has to be considered seriously.

8 Conclusion

This study wanted to assess the effects of China's 2018 plastic waste import ban on Italy's domestic waste management system, with a focus on the correlation between the volume of waste treated and the incidence of waste-related fires. The results, while partial, point to a worrying trend: an increase in the amount of waste processed, particularly after the disruption of important international trade flows, coincides with a notable rise in fire events near treatment facilities. Although a precise causal relationship is difficult to establish due to several data limitations, the evidence collected shows a picture of Italy's systemic unpreparedness in managing plastic waste sustainably and safely.

One of the primary limitations of the analysis lies in the level of data aggregation. The available data refer to total treated waste, without distinction between plastic and other waste streams, thereby introducing noise into the estimates. Likewise, data on regional waste production and exports are not disaggregated, further weakening the ability to isolate the specific effects of the import ban, object of the analysis. Moreover, the fires included in the analysis are only those officially reported and cataloged, suggesting that the true scale of the phenomenon may be different.

Nonetheless, the statistical association between treatment volumes and fire frequency persists even under conservative assumptions. Overall, although the estimated coefficients did not reach conventional levels of statistical significance, the consistently positive direction of the interaction term and post-treatment effects aligns with theoretical expectations and suggests that the Chinese import ban exerted upward pressure on domestic waste facilities. Both the temporal trends and the descriptive statistics reveal a clear upward shift in treated volumes post-ban, which supports the hypothesis that the sudden collapse of a major node in the chain overloaded the domestic waste system.

The specific analysis on fire events produced more robust and statistically significant findings. Using a negative binomial model to account for specific structure of the data, the study demonstrated a clear and positive association between the amount of waste treated and the likelihood and frequency of waste-related fires. In particular, the findings showed that an increase in the volume of waste treated is associated with a measurable rise in the expected number of fires.

Beyond the core variable of treated waste volume, the analysis reveals meaningful insights from the control variables included in the empirical models. Notably, the isolation variable, measuring the distance of each facility from the nearest other waste plant, shows a positive and statistically significant association with the incidence of fires. Equally significant is the effect of the export ratio, calculated as the share of regional waste exported relative to the amount produced. The analysis indicates a strong and negative relationship between export capacity and fire frequency. This finding implies that the ability to redirect waste outside the local treatment system reduces the likelihood of mismanagement and environmental hazards inside the country. The final suggestion is that the accumulation of poorly managed waste, intensified by sudden changes in export dynamics has tangible and dangerous consequences for local environments and public health.

Finally, the overview on the particulate matter emissions in Italy highlights both substantial progress and persistent challenges, from a more general and broader point of view. While overall emissions have declined markedly over the past decades, non-industrial combustion, including fire events and illegal waste burning, remains the dominant source and a pressing concern. The persistence of this sector underscores the need for continued monitoring and targeted interventions, as fire-related pollution generates not only acute health risks but also longer-term economic and social consequences. Addressing this issue will be central to advancing both environmental protection and public well-being.

Beyond the environmental dimension, this issue raises important economic considerations. While this thesis focused on the link between waste management capacity and pollution events, further research should explore the broader economic impacts of these environmental shocks. In particular, future studies could examine how increased exposure to air pollution, resulting from the rise in waste related fires, affects labor outcomes in Italy and across Europe. Such investigations would contribute to a more comprehensive understanding of the true cost of inadequate waste governance which are often not adequately considered.

The findings of this research underscore the urgent need for Italy to invest in more transparent and ecologically sound waste management systems, or in more resilient and sustainable export partnerships. In fact, the current situation can not be the permanent solution. The actual trades may temporarily reduce the environmental burden within the country, but can create significant economic and ecological imbalances globally. Overall, the challenge of plastic waste is not only a matter of environmental concerns, but it also has serious economic and social implications. Addressing it effectively requires an integrated approach that recognizes the interconnectedness of ecological degradation, public health risks, and economic performance.

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A Appendix: Figures and Tables

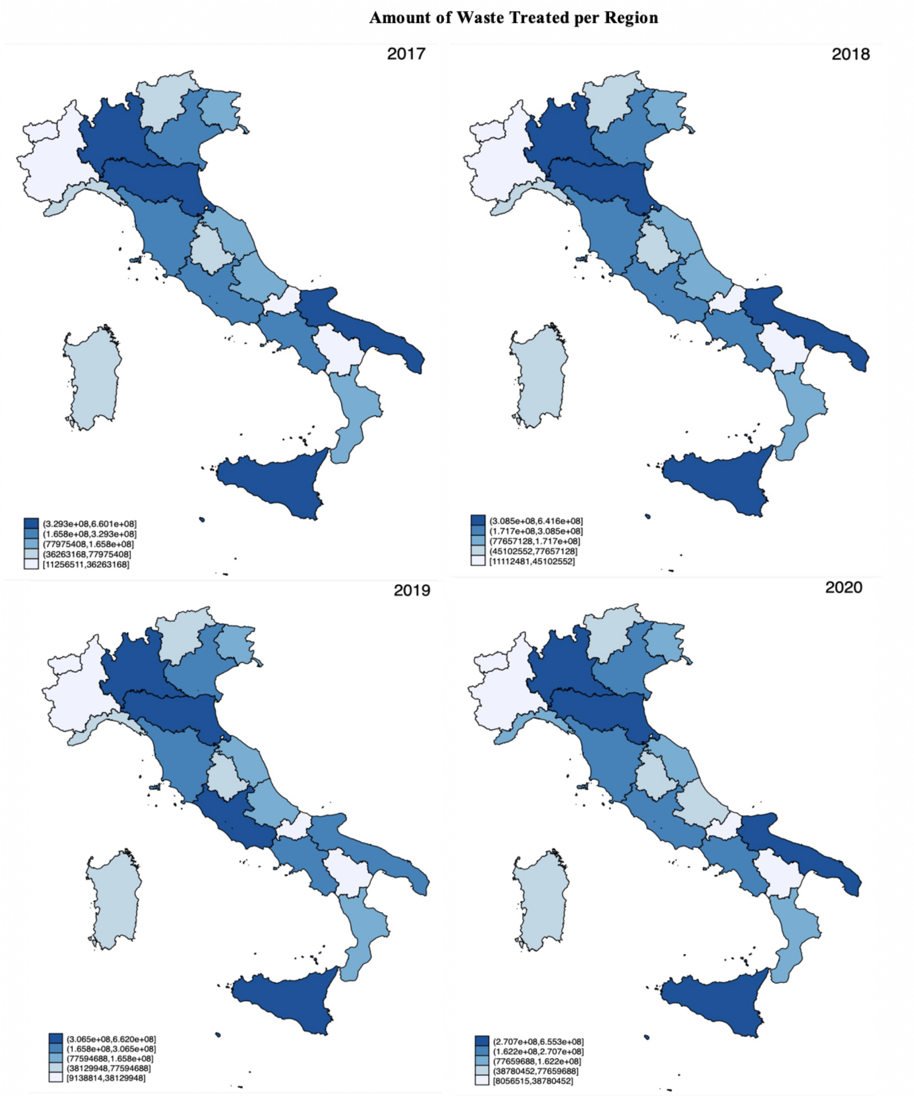

Figure 18: The map shows the regions in which the greater amount of waste is treated. The most affected regions are: Lombardia, Emilia-Romagna, Puglia and Sicily. There are not relevant changes throughout the years.

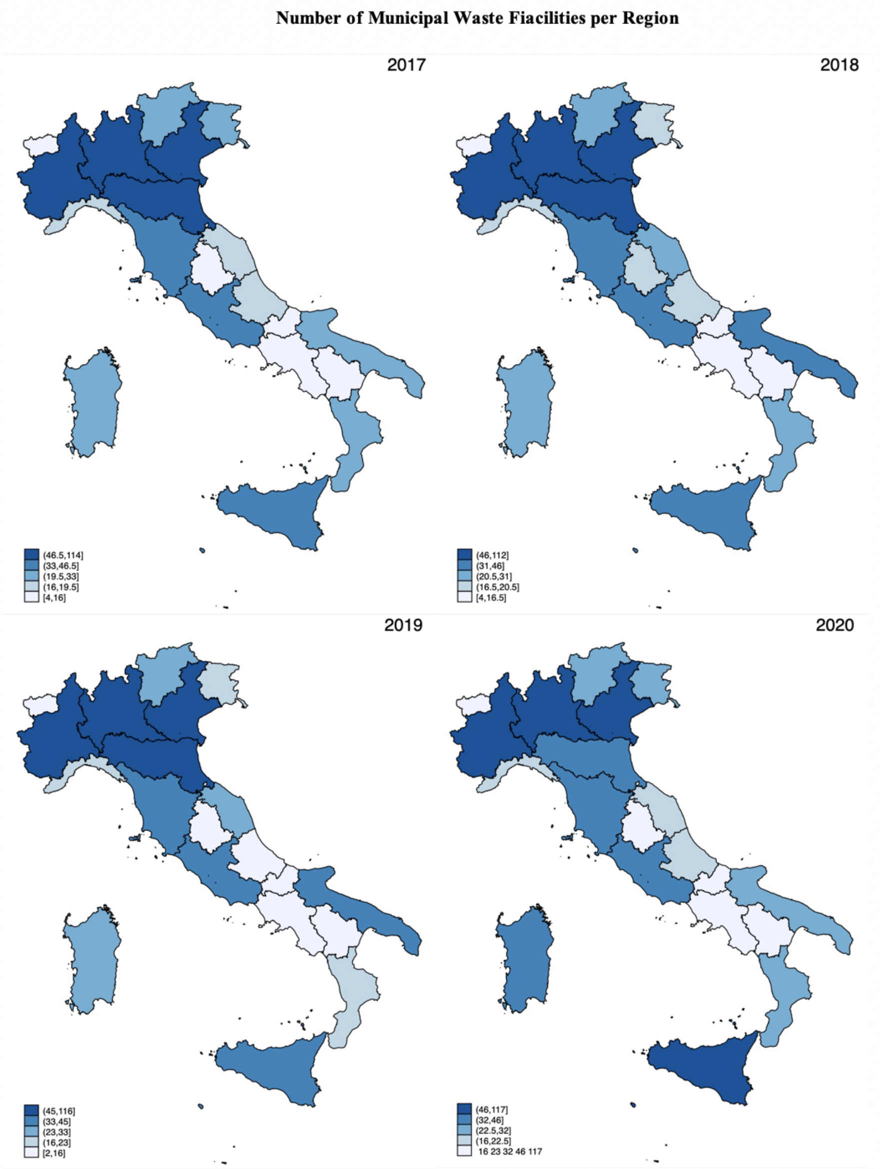

Figure 19: The map shows the number of municipal waste treatment facilities in each region and how this number changes over the years.

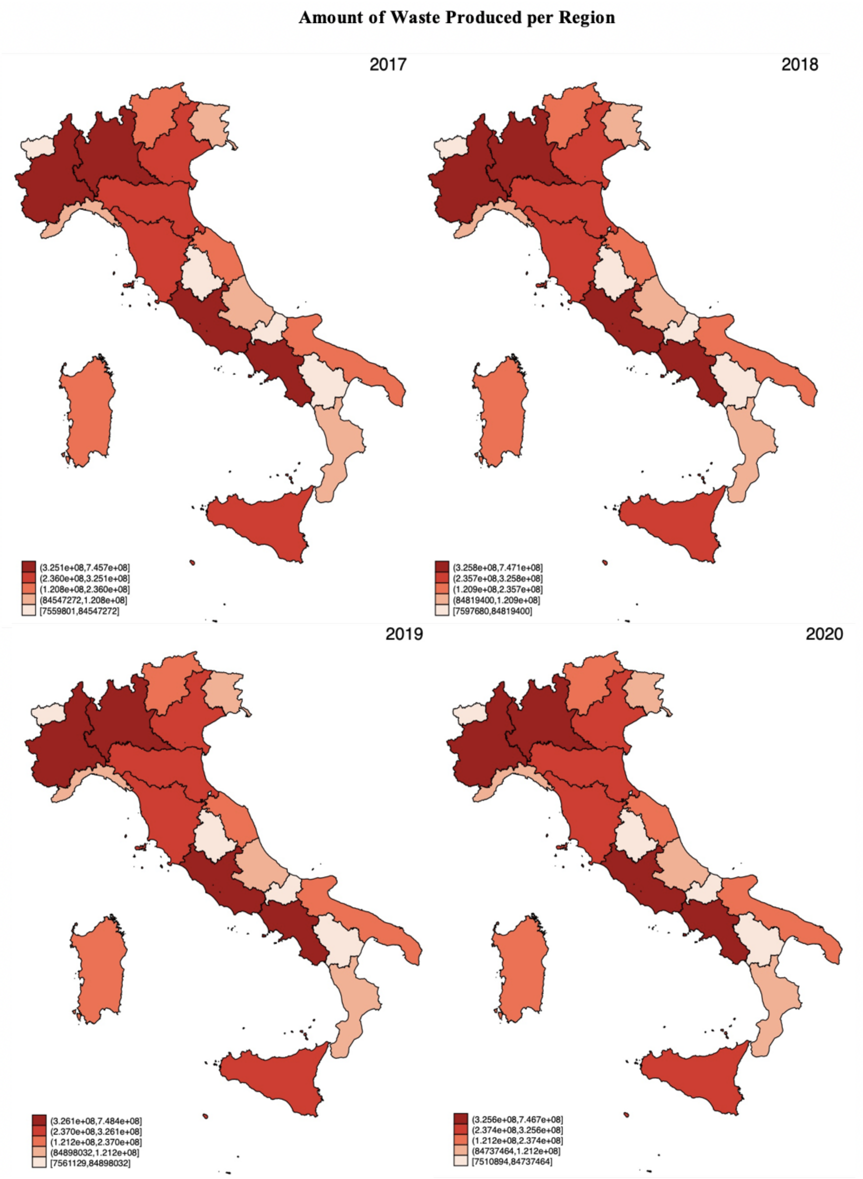

Figure 20: The map shows the regions in which the greater amount of waste is produced. The most producing regions are: Lombardia, Piemonte, Lazio and Campania. There are not relevant changes throughout the years.

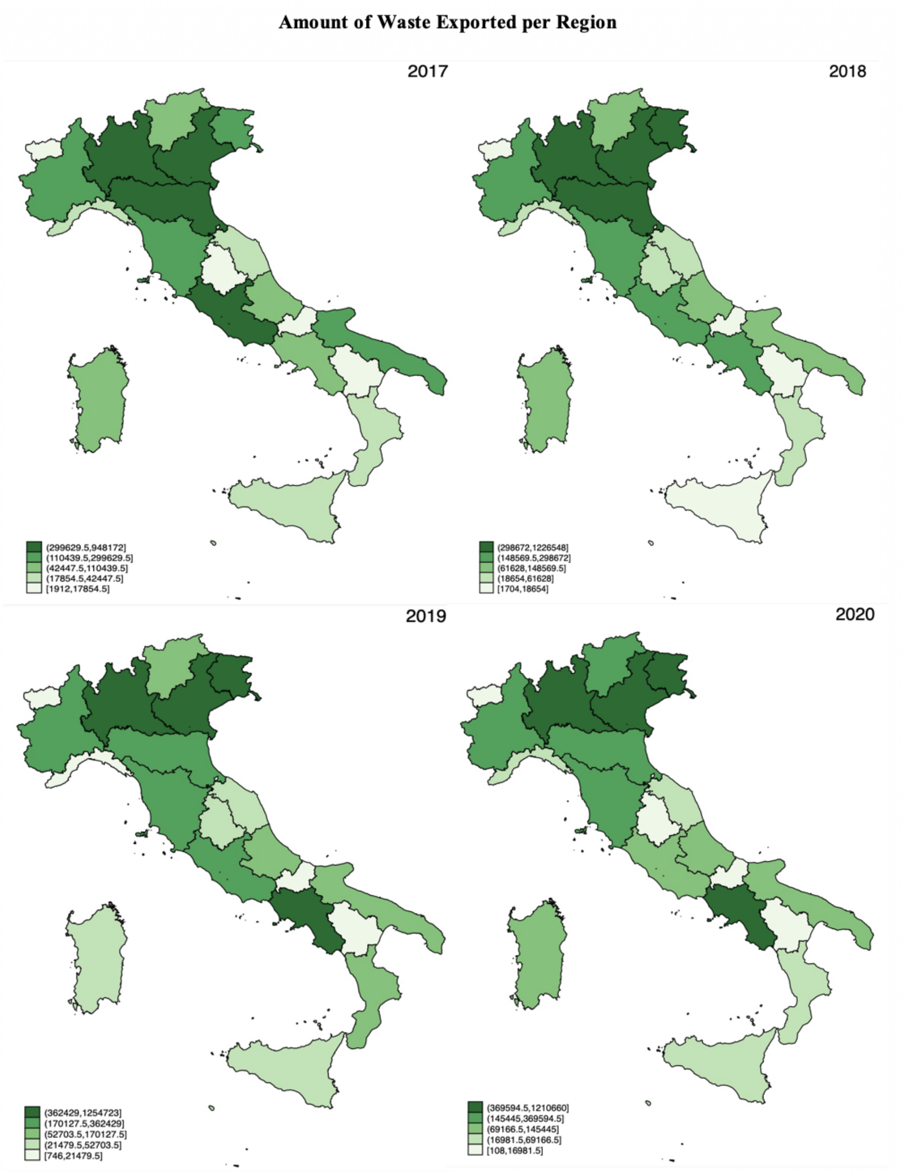

Figure 21: The map shows the regions in which the greater amount of waste is exported outside of Italy. There are some changes across the years; for instance Emilia-Romagna reduces its export after 2018, while Campania increases them in 2018 and 2019. These are total waste exports and, as in the case of total waste export data for the country, the effect of the China ban is not visible.