Università degli studi di Padova

Department of Economics and Management "Marco Fanno"

Master's Degree

in

Economics and Finance

The Effects of Eligibility Criteria to Government Subsidies on Corporate Behaviours

Supervisor: Prof. Amedeo Pugliese

Graduand: Chiara Cheli

2092562

A.Y. 2023-2024

The Effects of Eligibility Criteria to Government Subsidies on Corporate Behaviours

Master's Thesis

presented to

School of Economics and Political Sciences
Department of Economics and Management "Marco Fanno" - *d*SEA

in partial fulfillment
of the requirements for the Degree

Master of Science
in
Economics and Finance

by

Chiara Cheli

Academic Year
2023-2024

Declaration of Authenticity

Dichiaro di aver preso visione del "Regolamento antiplagio" approvato dal Consiglio del Dipartimento di Scienze Economiche e Aziendali e, consapevole delle conseguenze derivanti da dichiarazioni mendaci, dichiaro che il presente lavoro non è già stato sottoposto, in tutto o in parte, per il conseguimento di un titolo accademico in altre Università italiane o straniere. Dichiaro inoltre che tutte le fonti utilizzate per la realizzazione del presente lavoro, inclusi i materiali digitali, sono state correttamente citate nel corpo del testo e nella sezione 'Riferimenti bibliografici'.

I hereby declare that I have read and understood the "Anti-plagiarism rules" approved by the Council of the Department of Economics and Management and I am aware of the consequences of making false statements. I declare that this thesis has not been previously submitted – either fully or partially – for fulfilling the requirements of an academic degree, whether in Italy or abroad. Furthermore, I declare that the references used for this work – including the digital materials – have been appropriately cited in the text and in the "References" section.

Signature

Chiara Cheli

Abstract

Policy interventions such as taxation, subsidies, and accounting rules can incentivize firms to adopt certain behaviours to become eligible for preferential regimes. By categorizing firms as eligible and non-eligible, this thesis examines how the latter group may adjust their actions to appear compliant with benefit requirements.

More in detail, focusing specifically on the New Sabatini program in Italy, this thesis assesses whether firms categorized as non-eligible engage in size management to qualify for the subsidy benefits, particularly those near the eligibility thresholds. In addition, this research explores the long-term effects of such adjustments on the firms' performance.

Contrary to common findings in the literature, the results reveal that the New Sabatini program did not significantly drive bunching behaviour. Therefore, non eligible firms close to the threshold did not have a higher likelihood of obtaining the subsidy nor securing larger grant amounts, and no significant effects were observed on long-term performance metrics. This suggests that the New Sabatini's structure may not have been strong enough to encourage substantial financial adjustments, aligning with the program's design, which only requires firms to meet thresholds at the application stage.

Acknowledgments

Inizio con il dedicare questi mesi di impegno a Padova. La città che due anni fa mi ha accolta piena di speranze e aspirazioni per il futuro, che mi ha donato l'opportunità di scoprimi un po' di più nella nebbia che la contraddistingue e che fin da subito è diventata un luogo da poter definire casa. Devo ammettere però questa città ha fatto solo da cornice, la grande differenza è data dalle persone che mi sono state vicine. Inizio quindi con il ringraziare la mia famiglia, di sangue e non, che mi ha supportata durante la magistrale, che è stata presente ad ogni mio ritorno o partenza e che da sempre mi incoraggia a sognare in grande.

Ringrazio molto il mio relatore per le opportunità che mi ha offerto e per i preziosi suggerimenti che mi ha fornito

Ringrazio Carlo che mi è stato affianco in questi due anni spesi tra Padova, Germania e Bergamo e che più di tutti ha condiviso con me questo ultimo giro di montagne russe, nonostante soffra di vertigini.

Ti ringrazio perché hai avuto la pazienza per ascoltarmi, delicatezza nello spronarmi e tanto coraggio sia nell'assecondare che nel prendere parte alle mie idee strampalate.

Un grazie speciale ai miei compagni di corso che sono diventati molto di più di questo. Mark, Alice, Sona, Giulia e Marieline, siete stati compagni di risate, amici con cui condividere paure e desideri, sempre guidati dal pensiero che "l'unico limite sia il cielo".

[Thanks to my colleagues, who became more than that. Mark, Alice, Sona, Giulia e Marieline, you have been friends with whom I could share laughs, fears and dreams, always guided by the belief that "the only limit is the sky".]

Ringrazio poi i miei due carissimi amici, Paolo e Rachele, che fanno sempre il tifo per me, anche da lontano. Quando mi sento persa, riuscite sempre ad indicarmi la strada senza giudizi ma con grande empatia.

Un grazie poi alle amicizie di una vita che ci sono state e mi hanno ascoltata durante

lunghe passeggiate, così come quelle nate in tempi più recenti dall'esperienza in Olanda e poi da quella in Germania. Vi ringrazio perché spesso credete in me e nelle mie potenzialità più di quanto non lo faccia io.

Contents

List of Figures

List of Tables

1 Introduction

Considering the significant impact of government measures on public finance and the overall large number of beneficiaries, the empirical literature has extensively studied the effects of size-based requirements to qualify for policies such as taxation, subsidies, and accounting rules. A central finding is that these measures can induce firms near the threshold to adjust their behaviour strategically, potentially distorting market competition and resource allocation.

For example, Almunia and Lopez-Rodriguez (2018) found that a substantial number of firms strategically under-report their revenues to remain just below the large taxpayer unit threshold, thereby avoiding stricter monitoring. Moreover, Bernard et al. (2018) demonstrated that approximately 8% of firms, which would otherwise be above the regulatory threshold, actively reduce their reported size to avoid income statement disclosure. On average, these firms are found to sacrifice about 6.5% of total assets and 7%–9% of income to avoid disclosure requirements.

This behaviour highlights how firms around the regulatory cutoffs may alter financial reporting or limit their size to minimize compliance costs and administrative burdens associated with crossing the threshold, thereby qualifying for preferential regimes.

Italy represents a case of study both because of the information availability and the number of subsidies. Regarding the first aspect, the Italian National register makes available to the public the details concerning the subsidies, as the type, amount and purpose, matching them with the specific beneficiaries.

Next, from 2017 to 2019, a total of 2,836 government subsidies were offered, showing a growing trend over these years. Specifically, 753 different kinds of subsidies were offered in 2017, increasing to 1,436 in 2018, and reaching 1,647 in 2019. These measures, such as the "Fondo di Garanzia per le piccole e medie imprese" and "Nuova Sabatini- Finanziamenti per l'acquisto di nuovi macchinari, impianti e attrezzature da parte delle piccole e medie imprese - Versione modificata da Codice CE SA.47180", primarily aim to support small and medium enterprises (SMEs) through guarantees or grants for various investments. Additionally, several subsidies are then designed to reduce unemployment by incentivizing firms to hire individuals who are considered less favorable in the job market, such as disabled workers, women, or unemployed people. In this case, the incentives often come in the form of a reduction in the worker's social security tax burden. Another significant portion of the subsidies focuses on supporting firms in training their employees.

Therefore, this research aims to explore the impact of imposing criteria in Italy, particularly financial thresholds, on various corporate behaviours as well as the general effects on peer companies in terms of resource allocation.

The starting point is a distinction between compliant and non-compliant firms. Non-compliant firms are those that are not eligible but may exploit policy advantages, by engaging in opportunistic behaviors to appear eligible for policy benefits. Thereby, the research question driving this thesis is whether government subsidies affect firms' financing behavior. Specifically, it seeks to determine if non-compliant firms gain a competitive advantage by maximizing their eligibility for policy support, negatively impacting compliant firms.

Secondly, this thesis aims to study the broader implications of policy-imposed criteria on corporate behavior and market dynamics, focusing on the distinction between compliant and non-compliant firms and their competitive interactions. This research will provide insights into the firms' performance changes in the long run in response to size-based regulations.

To test the research question, the empirical approach relies on the assumption that a change in corporate behavior in response to regulation can be observed with bunching. This phenomenon can be identified by observing abnormal firm density around the threshold, indicating that firms are adjusting their behaviour to meet eligibility criteria, and within the bandwidth set by the regulation. (See Saez (2010) Kleven and Waseem (2013) and Kleven (2016)). In this context, some non eligible firms are expected to adapt their behavior to fall below the threshold, thereby becoming eligible for the preferential regime. By analyzing the distribution of firms around these thresholds, it is possible to assess the extent to which firms are engaging in such strategic behaviour can be inferred.

More in detail, this research examines the strategic behaviour of firms in response to the eligibility criteria of the New Sabatini subsidy, focusing specifically on the phenomenon of *bunching*, as observed by unusual concentrations of firms just below eligibility cutoffs. The analysis centers on two financial thresholds: the €43 million Total assets and the €50 million sales, as meeting either of these thresholds qualifies a firm for the subsidy.

Then, the announcement in 2015 of structural changes of the New Sabatini program, including increased available resources and faster grant processing, provides a natural setting to explore firms' behavioral adjustments.

A key consideration is then the time lag between financial statement periods and the application date, which may introduce timing frictions for firms regarding the timing of size adjustments. (See Kleven (2016) Gelber et al. (2014)).

The analysis aims to examine two key hypotheses, first, whether firms near the eligibility thresholds engage in size management in 2015 or 2016, such as strategic financial adjustments in response to regulatory criteria, to qualify for the New Sabatini in 2017 or 2018.

Secondly, whether bunching behaviour has long-term implications on the performance of firms. Specifically, firms that strategically manage their size to qualify for the subsidy may show differences in performance indicators.

The financial data are retrieved from the Orbis database, while the details regarding the New Sabatini from the Italian National register of aids.

Firstly, a graphical analysis was used to visually identify bunching around the €43 million total assets threshold and the €50 million sales threshold. In detail, firm distributions in 2014, prior to the reform, are compared with distributions in 2015 and 2016. There are indeed spikes in the density of firms below the thresholds in 2015 and 2016, which are interpreted as evidence of strategic adjustments in response to the policy change.

To quantitatively test the first hypothesis, a logistic regression model is used to assess whether firms identified as "bunchers" in 2015 and 2016 exhibit a higher likelihood of receiving the New Sabatini subsidy in 2017 and 2018 compared to those already below the thresholds. Control variables and fixed effects for firm characteristics are included, as to isolate the effect of bunching behaviour on the likelihood of receiving the subsidy.

For further insight, pooled OLS regressions estimate whether firms that bunch in 2015 or 2016 receive larger grant amounts than naturally eligible firms. Here, the dependent variable is the natural logarithm of the subsidy amount plus 1, and the model includes controls for firm size, financial indicators, and other factors influencing grant size. In both models several bandwidths are used.

To explore the second hypothesis, a difference-in-differences (DiD) model is used to analyze the long-term impact of bunching behaviour (in 2015 or 2016) on firm performance from 2017 onward, specifically EBITDA and adjusted ROA, following the empirical work of Gunny (2010). By comparing the pre - and post - policy announcement performance of bunching and naturally eligible firms, this model assesses whether size manipulation for eligibility results in sustained performance differences.

Furthermore, robustness checks are incorporated through the inclusion of alternative bandwidths and controls to ensure the reliability of findings across different model specifications.

The findings shows that firms that engage in bunching behaviour do not show a statistically significant increase in the likelihood of receiving the New Sabatini subsidy or a higher grant amount compared to the naturally eligible firms. Although the graphical analysis displays evident spikes close to the thresholds in 2015 and 2016, thereby suggesting some strategic adjustments, the logistic and OLS results do not confirm that these changes are driven by the New Sabatini.

The difference-in-differences analysis also reveals no long-term performance gains for bunching firms. Firms that engaged in size management to qualify do not demonstrate neither higher or lower EBITDA or adjusted ROA in subsequent years, suggesting that the New Sabatini reform did not sufficiently incentivize firms to pursue eligibility through substantial adjustments.

This research makes several contributions regarding the literature on firm behaviour, regulatory thresholds, and the economic impact of subsidy programs. By focusing on the New Sabatini subsidy in Italy, it provides new insights into how firms respond to threshold-dependent policies, particularly examining whether firms strategically manage their size to qualify for government benefits. Aligning with findings from studies on threshold effects of (Harju et al. (2016) and Klimsa and Ullmann (2022)), this study reports no significant effect of bunching, which adds evidence to the broader literature of tax and subsidy-induced behaviour and the impact of size-dependent regulations. However, additional research could further investigate the impacts of other subsidy programs on firm behaviour, helping to understand the drivers behind such responses.

Additionally, this study contributes to the studies focused on the design of size-dependent regulations. The New Sabatini program's eligibility requirements need only to be met at the time of application, rather than being continuously enforced. This flexibility allows firms to grow without the restrictions of maintaining eligibility post-application, which reduces long-term distortions. Indeed, those may arise when firms intentionally limit their growth to remain eligible for benefits. This dynamic enriches the literature on policy design, illustrating how temporary requirements may avoid creating persistent and detrimental distortions in firm behaviour.

2 Theoretical Framework

2.1 Subsidies: nature and classification

A subsidy is a form of government intervention designed to provide financial assistance to a specific group of beneficiaries, added to the primary goal of promoting desirable economic and social outcomes. According to Schwartz and Clements (1999), subsidies can take various forms, including direct payments such as cash grants, credit incentives like guarantees, tax subsidies, government equity participation. Again, there are in-kind measures that allow the provision of goods or services below the market prices, or procurement subsidies where the government purchases goods or services at above-market prices, lastly regulatory incentives that alter market dynamics.

The primary objective of subsidies is to reallocate resources in a way that promotes a more efficient and equitable distribution within the economy. Schwartz and Clements (1999) identify three key justifications for the use of subsidies. First, they can tackle market imperfections, as for example the free-rider problem associated with innovation, or information asymmetries that characterize the credit markets. Second, subsidies enable firms to overcome initial cost disadvantages, helping them achieve economies of scale. Finally, these measures support the promotion of social objectives, including income redistribution and the reduction of unemployment. (See Huang (2022))

Since the government and taxpayers are key stakeholders, as they are the primary financiers of subsidies, evaluating the efficiency of these subsidies is a complex process that requires careful consideration of various factors see (Schwartz and Clements (1999). One critical aspect is the transparency during the allocation and administration of subsidies. Greater transparency reduces the risk of misuse by recipient firms. That is why, subsidized firms are often subject to more stringent disclosure requirements, which facilitate the monitoring of how firms utilize the subsidies. (See Huang (2022)). Furthermore, subsidies should be periodically reassessed to ensure that they remain cost-effective and continue to address the intended objectives. This involves adapting the subsidy programs to evolving economic conditions and needs, as in this way it is possible to avoid long-term dependency and market distortions. (See Klimsa and Ullmann (2022) and Schwartz and Clements (1999)).

While subsidies are designed to improve efficiency and equity, empirical evidence on their effectiveness is mixed. Some studies highlight the potential for efficiency losses and unintended consequences, such as overproduction or misallocation of resources, which can undermine the intended benefits of subsidies. (See Di Marzio et al. (2024) and Acharya et al. (2022)).

2.2 Bunching and threshold-based regulations

Threshold-dependent regulations, as subsidies or tax advantages, typically impose financial requirements like revenue, profit, total assets, taxes, or number of employees that firms must meet to qualify. For instance, empirical studies widely documented how firms, or individuals, cluster just below or above the qualifying thresholds. (See Kleven (2016)). So that, firms which meet these criteria qualify as compliant and can access the benefits, while those exceeding these thresholds are categorized as non-compliant and ineligible. (See Klimsa and Ullmann (2022)).

A possible consequence is that, although these thresholds are intended to simplify regulatory enforcement and target specific groups, they can create unwanted incentives for firms to manage their size or operations strategically to avoid crossing these limits and meet in this manner the requirements. The behavior is known as "bunching", whereby firms or individuals near the threshold adjust their financial reports to maximize eligibility benefits. Consequently, bunching often occurs as a response to the introduction or change in a tax or subsidy policy.

The bunching analysis relies on the studies of Saez (2010), Chetty et al. (2011) Kleven and Waseem (2013), who developed frameworks to examine economic behavior in response to thresholds-based policies. Their studies used administrative data, that were more available than previously and provided insights into the effects of the imposition of thresholds on the decision-making process.

The literature examined first to responses to kinks points, which are discontinuities in marginal tax rate, such as a discrete increase of the tax rate that creates a convex kink in the budget constraint. (See Saez (2010)). More in detail Saez (2010) considers a model where individuals maximize their utility over two goods, pre - tax income, which negatively affects utility as require effort, and post - tax income, which related positively.

Where there is an increase in the marginal tax rate at a certain income level, the slope of the linear budget in that point suddenly shifts for instance from $1 - t$ to $1 - t - \Delta t$. So that not all the individuals are affected, but only those who had a point of maximum above the kinks. The result is that they may adjust their earnings downward to maximize their utility. This behavior creates a spike in the earnings distribution around the kink, reflecting an adjustment to the marginal tax increase. (See Saez (2010)).

Kleven and Waseem (2013) extended the analysis to notches, which can be defined as discontinuities in the average of tax rate. Differently from kinks, notches create a larger incentive for bunching as there is a sudden jump in the tax burden or subsidy eligibility when crossing the thresholds. Assuming an increase in the average tax rate at a certain income level, individuals or firms around the point face a discrete choice, either moving below the notch to retain a lower tax rate or remaining above and pay higher tax liability. Due to the maximization utility, notches create strictly dominated regions in the choice set, which means that being located above becomes unfavorable. This brings to the creation of a bunching mass immediately below the threshold, while the area above the notch shows a hole in the distribution. (See Kleven (2016)).

Regarding firms behavior, when regulatory or subsidy thresholds are based on their size, their utility function may change. The result is that some firms have an incentive to manage to stay just below. This bunching behavior is evident when regulations offer benefits for firms below certain size limits, as managers may respond by adjusting earnings. (See Dichev et al. (2013) and Gelber et al. (2014)).

2.3 Incentive for size management

More in detail, a growing literature has examined the effects of size-dependent policies on firm behaviour, as well as the broader impact of such regulations on aggregate productivity. The rationale behind size management is rooted in the economic principle of cost-benefit analysis. As when the costs of complying with regulations that apply above certain thresholds outweigh the benefits of growing beyond those thresholds, there is an incentive for firms to manipulate their size to stay below the regulatory limits. Therefore, non-compliant firms prefer not to evolve but to sacrifice part of their productivity, total assets or both to gain benefits from the policy. (See Bernard et al. (2018) and Di Marzio et al. (2024)).

Size management can be carried out first of all through earnings management, which includes for instance the management of accruals management and real activities. The first one involves the choice of specific accounting methods to report operating activities without actually changing them. On the other hand, real activities manipulation affects the actual structure or timing of operations and investments. For instance, by decreasing R&D expenses, adjusting the timing of the fixed assets sales, or overproducing to reduce the unit costs. (See Dichev et al. (2013), Roychowdhury (2006) and Gunny (2010)). Evidence also highlights that these forms of earnings management are effectively used to meet some benchmark (See Gunny (2010)).

In line with these findings, an empirical study focused on European firms demonstrates that many managed their size strategically to stay below regulatory cutoffs, thereby avoiding stringent disclosure requirements and mandatory audits. In detail, the actions taken may involve splitting business investments, reducing or reallocating the assets. Indeed, by analyzing the distribution of firms around the required thresholds, the study reveals an abnormal density of firms just below the cutoff points. Specifically, the findings show that approximately 8% of firms manage their size downward to avoid increased disclosure requirements, sacrificing an average of 6.5% of their asset and a 7%-9% of income. (See Bernard et al. (2018)).

Another way that firms use to manage their size is under-reporting revenues or profits. Indeed, the study by Almunia and Lopez-Rodriguez (2018) shows that firms report revenues below the cutoff to evade stricter tax enforcement. Similar research in Italy has leveraged the variation in cutoff points over time and across industries to analyze changes in firms' marginal utility, using bunching rates as an indicator of tax evasion. The results demonstrate significant bunching responses mostly driven by under-reporting, difficult to justify solely by adjustments in labor supply or production. (Di Marzio et al. (2024)).

The consequences of such behaviour goes beyond the specific firms which engage in size management. Indeed, as less productive firms are subsidized, those above the thresholds are affected as well. For instance, firms in the above area may face higher costs, thus risking to exit from the market, as shown by Di Marzio et al. (2024). This dynamic can result in distorted prices and wages, with possible long-term effects on economic growth and productivity. (See Acharya et al. (2022)).

Furthermore, Gourio and Roys (2014), while examining distortions caused by employees thresholds, found that such thresholds indeed lead to misallocation of the labour force, however the impact on the overall economic productivity was limited.

Moreover, it is important to note that the presence of government policies, such as subsidies, does not lead necessarily to distortions. The key lies in how the regulations are designed. Indeed, a study conducted on Chinese firms by Xu et al. (2022) suggests that, for example, the efficiency of subsidies differs depending on the life cycle stage of the enterprise. On one hand, the findings indicate that mature firms may report drops in the performance due to the increase of production without corresponding investments in R&D. On the other, start-ups may benefit from subsidies, in this way improving innovation and productivity.

Therefore, adapting subsidies depending on the firm's stage could maximize outcomes while avoiding inefficient allocation of resources. (See Xu et al. (2022)).

3 Institutional setting

3.1 Subsidy Programs in Italy: Overview and Criteria

After computing the number of firms that benefited from Italian subsidies, by counting only those with a value greater than zero and treating firms with multiple subsidies as a single entity, an examination of subsidy data reveals that the number of beneficiaries prior to 2017 was comparatively limited (see Figure 12, 13, 14 and 15). Thereby, the focus in on the period going from 2017 to 2019 (see Figure 1, 2 and 3).

In detail, in 2017, 116,766 distinct enterprises benefited from 753 different subsidies. Then in 2018, there was a increase in both the number of beneficiaries and the number of unique subsidies compared to the previous year, with 326,064 firms benefiting from 1,436 subsidies. Lastly, in 2019, while the number of unique firms slightly declined to 281,028, the number of total subsidies increased to 1,647. (Registro Nazionale degli Aiuti di Stato (2024))

Figure 1: Beneficiaries in 2017

Over these years, similar forms of assistance were provided to support small and medium-sized enterprises (SMEs), facilitate training, promote the employment of disabled workers, and tackle the consequences of natural disasters. Considering that Italy's economic structure is predominantly composed of small and medium-sized enterprises (SMEs), which in 2014 counted for the 80% of total employment and 67% of value added, as reported by OECD

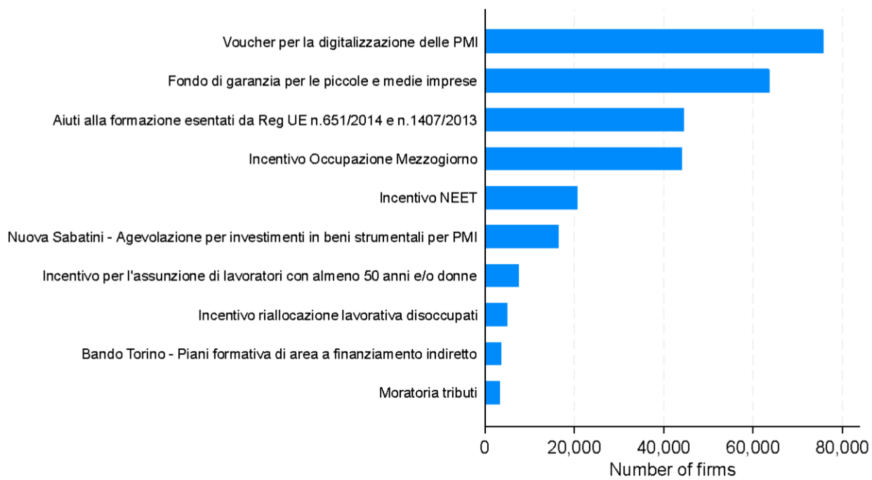

Figure 2: Beneficiaries in 2018

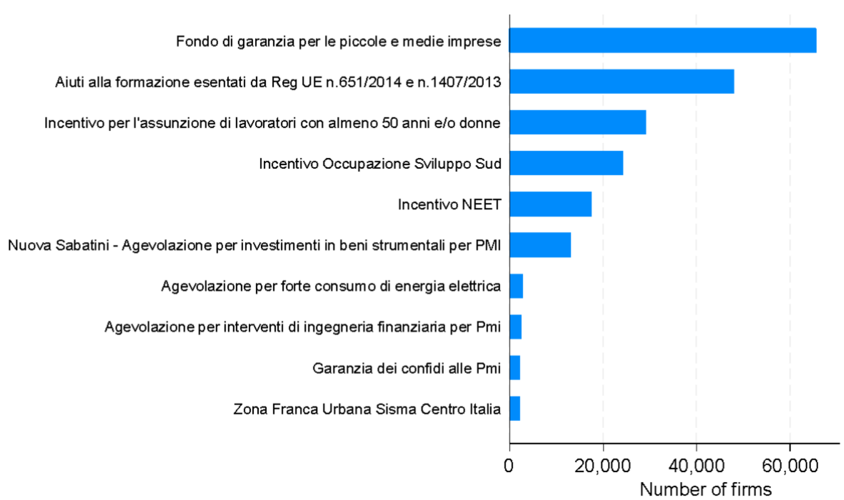

Figure 3: Beneficiaries in 2019

(2014), it is evident that most regulatory measures are designed to support SMEs.

More in detail, key programs, such as the Fondo di Garanzia and Nuova Sabatini, offered grants typically non-repayable to enhance SMEs productivity through investments in new machinery, technology, and infrastructure. Precisely, these grants accounted for a significant share of Italian SMEs support, aligning with the main purpose to boost SMEs competitiveness. Other targeted programs included social security reductions, to encourage the hiring of disadvantaged workers, and disaster aid for regions affected by the 2016–2017 central Italy earthquakes. For this reason, the eligibility criteria were primarily based on the type of employees and the hiring process rather than financial indicators.

The majority of these subsidies were financed by the National Institute for Social Security (INPS), the Ministry of Enterprises and Made in Italy and regional funds.

Eligibility requirements for the natural disaster subsidies included evidence of a reduction in total sales and proof that the firm's headquarters were located within the affected municipalities. For social security reductions, eligibility was based on the type of employees hired and the hiring process rather than on financial indicators. The criteria for SME-focused programs, such as the Fondo di Garanzia and Nuova Sabatini, have remained consistent over the years, aligning with the general standards for SME classification.

Specifically, from the 1st January of 2005, Italy has introduced a new regulation to distinguish between small, medium and large firms, as declared by European Commission (2003). More in detail, according to the Italian law[1] firms are classified as small if they fall below the following thresholds: the number of employees equal to 50 and then either the total assets or sales lower than 10 million euros. While, medium firms must have the number of employees lower than 250 and either the total assets lower than 43 million euros or total sales lower than 50 million euros. For both small and medium firms, it is sufficient to meet the thresholds based on the most recent balance sheet. This latter classification, which distinguishes SMEs from large firms, is the unique threshold used by Italian authorities

[1]L. 18 aprile 2005, n. 62, *Disposizioni per l'adempimento di obblighi derivanti dall'appartenenza dell'Italia alle Comunità europee. Legge comunitaria 2004*, entrata in vigore: 12 maggio 2005.

to establish the eligibility for grants. Therefore, if there are any unusual patterns, as a concentration of firms just below these thresholds, it means that firms may be strategically adjusting their reported size or financial metrics to qualify specifically for subsidies.

Furthermore, always according to the same law, firms are categorized as stand-alone, associated, or subsidiary entities, which determines how their financial data should be presented for eligibility purposes. For associated firms, total assets, sales, and employees counts must be proportionally aggregated based on ownership share to accurately reflect the firm's scale.

3.2 The New Sabatini Program: Evolution, Requirements, and Policy Objectives

The New Sabatini program (Instrumental Goods Measure), launched by the Italian government and now managed by the Italian Ministry for Enterprises and Made in Italy, is a primary subsidy initiative aimed at supporting investments in purchasing machinery, equipment and technology.

The original Sabatini policy was introduced in 1965 with L.1329/65 [2], with the purpose of enhancing competitiveness and productivity of the Italian small and medium firms, by facilitating access to credit. Since its origination, the New Sabatini program has undergone several updates to adapt to Italy's economic landscape. For instance, some adjustments included differentiating interest rates, broadening the types of eligible investments and increasing the maximum loan amounts.

These reforms led to the creation of the "New Sabatini" program through D.L. 69/2013[3], then further modified by D.L. 3/2015.[4]

This analysis focuses on the most recent significant policy change, which was announced on January 24, 2015, enacted on March 24, 2015, and subsequently refined on January 25,

[2]LEGGE 28 novembre 1965, n. 1329, *Provvedimenti per l'acquisto di nuove macchine utensili*

[3]*DECRETO-LEGGE 21 giugno 2013, n. 69, Art 2*, *Disposizioni urgenti per il rilancio dell'economia*.

[4]*DECRETO-LEGGE 24 gennaio 2015, n. 3*, *Misure urgenti per il sistema bancario e gli investimenti*

2016[5].

First of all, prior the 2015 – 2016 reform, loans related to the New Sabatini were sourced only from a special fund managed by Cassa Depositi e Prestiti (CDP). While, after the reform, banks and leasing companies were allowed to extend loans to SMES from the CDP's fund or other private sources, allowing Smes to choose the most favorable financing plan. Moreover, the 2015 – 2016 reforms simplified the application and approval process significantly. The Ministry of Economic Development (MISE), banks, and SMEs could communicate more, reducing the documentation requirements and thus accelerating the application approvals.

The result of these improvements was evident on May 2, 2016, when applications reopened. There was a significant increase in demand, such that for September the resources were already ended. In response the Italian Government authorized additional refunding[6], reaching €943,86 million, and extended the application period from 2nd of January 2017 to 31 December of 2018.

To qualify for the subsidy in 2017, firms must meet specific criteria, related to financial thresholds, sector eligibility and investment types, at the time of the application process. First of all, the program was available exclusively to SMESs, defined as those with fewer than 250 employees and either annual sales not exceeding €50 million or total assets below €43 million.

Then, the investments must be new and tangible assets, categorized as "machinery and equipment", "industrial and commercial equipment," and "other assets." Software and digital technologies were also allowed, while expenses related to land, buildings or used items were excluded. Furthermore, the investments could not be simply a component of a larger

[5] *Circolare 23 marzo 2016, n. 26673*, *Termini e modalità di presentazione delle domande per la concessione e l'erogazione del contributo di cui all'articolo 6 del decreto interministeriale 25 gennaio 2016, recante la disciplina dei finanziamenti per l'acquisto di nuovi macchinari, impianti e attrezzature da parte di piccole e medie imprese*.

[6] *LEGGE DI BILANCIO 2017*, dicembre 2016, *Legge 11 dicembre 2016, n. 232*, VOLUME I, Articolo 1, commi 52-57 (Nuova Sabatini).

machinery but must be related directly to the operational activities of the company.

In general, the subsidy was structured as a loan provided by banks or financial intermediaries, which may cover the full investments and supported by another important subsidy, the "Fondo di Garanzia". In addition, the Ministry of Economic Development (MISE) offered a grant to cover part of the loan interest, calculated conventionally over a five-year period at standardized rates: 2.75% for standard investments, 3.575% for investments in digital or green technologies from 2017. The loan amount should have been between €20,000 and €2 million, with a duration of maximum five years.

The application process began with firms submitting their request through a bank or financial intermediary, which would assess eligibility based on provided financial statements and investment plans. The bank then submitted a formal request to the Ministry, which would confirm the availability of resources, and, after the approval, the intermediary would grant the loan, and the Ministry would issue a contribution that covers the interest component. The investments must be completed within 12 months from the date of the funding contract.

Throughout the loan period, SMEs were required to demonstrate their compliance, such as that the investment was operative. The Ministry was authorized to demand additional documentation and conduct audits to ensure that funds were used appropriately.

3.3 Relevance of the New Sabatini for Studying Firm Behavior and Strategic Adjustments

Between 2017 and 2018, the New Sabatini was among the ten most important Italian subsidies in terms of number of beneficiaries, contrary to the previous years. Between 2017 and 2018 a total of 21,937 were beneficiaries of the New Sabatini, obtaining an average of € 23,217 to cover the interests' portion. In addition, the Small firms represented the primary beneficiaries of this financial support. (See Ministry of Enterprises and Made in Italy (2017) and Ministry of Enterprises and Made in Italy (2018)).

Considering then the high relevance of the New Sabatini program within the Italian scenario, combined with the policy reform of 2015 - 2016 that resulted in an increase in the applications, there is the opportunity to analyze firm behavior in response to altered incentive structures. Despite the fact that the requirements are similar across several subsidies, the spike in applications and grant distribution in the post-reform can be exploited to examine if firms show a bunching response. In particular, the policy changes of $2015 - 2016$ allows us to explore bunching behavior, where firms adjust their financial statements, assets or other characteristics to meet the requirements. Such responses align with observations in similar studies where firms or individuals adjust to fall just below policy thresholds to gain benefits. (See Saez (2010) and Harju et al. (2016)). The increase in post-reform applications may indicate that some firms, especially those near the thresholds, may be likely to behave in this way.

A key aspect to consider, while analyzing their response, is the timing mismatch between the subsidy application and the financial statement submitted. The rule is that the financial statements must be presented within 30 days of approval to the Enterprises Register, recalling that the annual financial closures have to be within 120 days after the end of the fiscal year. For this reason, the result is that often firms apply with "old" financial statements. In addition, even though a firm applies in a specific year, not necessarily the grant will be received within the same fiscal period.

Therefore, to account for this dynamic, firms that receive the New Sabatini in 2017 and 2018 are likely to have applied based on financial statements from 2015 or 2016. This means that any abnormal response, as bunching behavior, would appear as in these earlier financials. From one hand, including these years means capturing both the immediate response in the year of the policy announcement and the period after. On the other hand, this approach allows a realistic picture of how firms gradually adapt their financial statements in response to the New Sabatini's requirements, because of potential frictions. Similar findings in earnings adjustments studies found that, however, the biggest alteration is found to be within three years. (See Gelber et al. (2014)).

3.4 Hypothesis Development

To investigate the influence of threshold-based subsidies on firm behaviour, this research examines the New Sabatini program, following a broad literature that explores bunching behaviour in response to both tax and non-tax incentives. The primary focus is on firms' strategic size management to meet subsidy thresholds and the long-term performance outcomes of such adjustments. The focus is on strategic management size and long-term performance outcomes.

The research question driving the analysis is:

How do firms respond to threshold-dependent subsidies and what are the long-term implications of strategic adjustments to qualify?

Whether firms in the sample have indeed altered their finances does not have an obvious answer. From one point of view, it is enough to meet one criterion – either sales or assets – making the qualification more feasible compared to settings where multiple adjustments would be required. Indeed, firms are more likely to make adjustments when they can manage one of multiple criteria to qualify. (See Klimsa and Ullmann (2022)

On the other, strategic adjustments can be imprecise and require time, particularly for firms whose financials are near the eligibility threshold. Firms may need to balance short-term benefits of qualifying against potential long-term losses in terms of growth. Thereby, this behavior can be seen as a "trade-off", due to the fact that firms weigh the benefits of receiving subsidies against the opportunity costs of limited growth. (See Bernard et al. (2018)).

However, to qualify for the New Sabatini is necessary to meet the criteria only at the time of the application, then the firms can fall into the large category.

Hypothesis 1: threshold- dependent subsidies, such as the New Sabatini, are associated with strategic size management, known as bunching.

As a wide literature on threshold-dependent subsidies suggest that firms have incentives to manage their finances, within the law, to meet the requirements, the same phenomenon is examined with the New Sabatini. This investigation will assess if Italian firms near the eligibility thresholds adjust their total assets or sales to apply. An absent association would mean that the subsidy is designed in a way that does not create an incentive for firms to manipulate.

Hypothesis 2: how is the performance of bunching firms in the long run? Is bunching beneficial?

The long-term effect of bunching is an open question. In the short-run, bunching may provide benefits by securing subsidies or tax advantages, but in the long it could cause growth losses. For instance, prior researches show that if policies encourage firms to remain small, the result will be a loss for the firm growth and the economy, due to the creation of distortions. (See Di Marzio et al. (2024) and Bernard et al. (2018)).

4 Data

To guarantee the consistency of the analysis, it is essential to take into account the timing mismatch between the grant application, the financial statement used as a reference, and when the firm will actually receive the grant. For this reason, the final sample includes the same unique firms' specifics stated for the years from 2014 to 2019, in the form of Company ID, year, financial data, and subsidy status. More in detail, the sample pictures the firms before, during, and after the announcement of modifications of the New Sabatini program, allowing for a detailed analysis of the firm's behavior and subsidy allocation over time.

The dataset was constructed from two primary sources. Firstly, the set of information about the beneficiaries of the New Sabatini was obtained from the Italian National Transparency Register. The platform is designed to ensure that public financial aids are administered openly. Therefore, it is possible to acquire detailed insights regarding subsidies, including the names of beneficiaries, the types of aid, the amounts granted, and the distribution of subsidies over the years and across sectors and regions.

In detail, after examining the volume of subsidies from 2013 to 2019, only data from 2016 to 2019 were retained. The period before 2016 was excluded due to the limited number of beneficiaries, and data beyond 2019 were omitted due to the COVID-19 pandemic, which significantly altered both the subsidy dynamics and economic conditions. However, considering the purpose of the analysis, only firms that received the subsidy in 2017 and 2018 were included. Indeed, these are the firms that received the grant after the changes in the regime. Then, these two years were aggregated into a single entry per firm, resulting in a cross-sectional dataset that reflects each firm's total subsidy amount over both years. This aggregation accounts for firms that received multiple grants within this period.

The second source used to retrieve the data was the Orbis database from Bureau van Dijk, which provides information about firm's financial and employment. In detail, the observations included in this second dataset are the Italian firms that fall within a 40% range around either the sales threshold or 46.5% around the assets threshold for at least one year between 2015 and 2019. These ranges were chosen to capture the firms' patterns around the cutoff points, as these are the firms that are more likely to exhibit bunching behaviour. The use of relatively wide bands is supported by previous studies on bunching, which suggest that firms tend to cluster around the thresholds (See Saez (2010); Chetty et al. (2011)). Therefore, this approach allows for a comparison of firms just below and just above the threshold, which are likely to be similar in many aspects, thereby helping to isolate the impact of manipulation on the subsidy allocation.

Moreover, the research strategy employed in Orbis filters for stand-alone firms (e.g. not belonging to any business group) to ensure that the sample accurately reflects the firm's individual financial performance.

Lastly, firms that omitted sales, total assets, or the number of employees, as well as firms incorporated after 2015, were excluded from the sample. These filters ensured that the dataset was balanced and that all firms had enough historical data. Companies in the financial and insurance sectors were also removed, as they are ineligible for the New Sabatini subsidy program.

The final step was the integration of the two datasets based on each firm's identification code. To address the timing mismatch, financial statements from 2015 and 2016 were matched with summarized subsidy information from 2017 and 2018, consolidated in the first dataset. The result was a panel dataset that included each firm's annual financial data and its subsidy status, allowing in this manner for a longitudinal analysis of financial behavior in relation to subsidy eligibility.

An initial analysis was conducted to identify and handle any missing data or anomalies, ensuring that the analysis was based on complete and reliable information. After applying the above filters, the final sample consists of firm-year observations, resulting in 11,497 unique firms that repeat from 2014 to 2019.

4.1 Descriptive Statistics

Starting from the dependent variables, *"sub"* is a dummy that equals 1 if the firm is a beneficiary of the New Sabatini program in 2017 and/or 2018. The variable *"ln_amount"* is the natural logarithm of 1 plus the grant amount obtained by the firm; if the firm received multiple grants, the variable reflects the sum of all amounts. This transformation normalizes the data. (Pappas et al. (2024)).

The *"ebitda"* variable represents the ratio of EBITDA (earnings before interest, taxes depreciation and amortization) to sales, which indicates a firm's operating profitability compared to its sales. Lastly, *"ADJROA"* is constructed by following the methodology of Gunny (2010), such as by adjusting each firm's ROA relative to the industry median ROA for that year and sector. This adjustment provides an industry-standardized view of firm performance, which offers a more accurate reflection of the impact of bunching.

The firms included in the sample differ in terms of financial characteristics, such as financial stability, operational efficiency and growth opportunities. To account for these differences, a set of control variables has been created. *"Firms_age"* is computed as the natural logarithm of 1 plus the number of years since the incorporation date, the variable gives an idea of the maturity of the firm, considering that older firms may potentially be more stable and gain more experience. (See Crouzet and Mehrotra (2020)). The *"ebitda"* computed as the ratio of EBITDA (earnings before interest, taxes depreciation and amortization) to sales, is also included among the control variables. The *"roa"* variable, calculated as EBITDA (earnings before interest, taxes depreciation and amortization) divided by total assets, measures the return on assets, as well as the profitability of the operations, such as how efficiently the company is using its assets to generate earnings. (See Penman (2013))

Moreover, *"cash holdings"* is the ratio of cash and cash equivalents to total assets, which indicates the firm's liquidity and its ability to meet short-term obligations. The *"Leverage"* variable represents total debt to total assets, providing insight into the firm's debt level compared to its assets baseline. (See Moreta (2024))

Then, *"Ln(sales)"*, which is the natural logarithm of total sales, is used to normalize the scale of sales and control for differences in firm size. "Ln(tot assets)" is the natural logarithm of assets, again used to normalize the distribution of the assets variable. Together with the natural logarithm sales, this variable ensures that size is accounted for. (See Moreta (2024))

The *"ROE"* variable, calculated as the ratio of the net income to total equity, shows the return on equity, which indicates the profitability of the firm compared to the shareholders' equity. The indicator gives a perception of how efficiently equity capital is being used to generate profits. While, *"Capital"* measures the ratio of capital compared to total assets, showing the proportion of firm's assets that are engaged in capital investment.

Finally, *"liquidity"*, computed as the ratio of current assets and current liabilities, measures the firm's ability to cover its short-term obligations. (see Moreta (2024), Penman (2013) and Pappas et al. (2024).)

In Table 2 and 1, it is presented a summary statistics for the control and dependent variables first within the 20% bins around the asset threshold, followed by the corresponding intervals around the sales threshold.

Around 20% of the 50 million sales threshold						
Variable	N	Mean	SD	p25	p50	p75
sub	11635	.045982	.209455	0	0	0
ln_amount	11635	.4965047	2.270457	0	0	0
AdjROA	11616	.0234217	.1051084	-.0229195	.0079412	.0575906
firms_age	11635	3.106675	.722178	2.70805	3.258096	3.610918
ebitda	11616	.0821895	.1123283	.0259019	.0570073	.1113667
roa	11616	.0934781	.105707	.0439183	.0773562	.1306848
cash	11545	.0905713	.1119847	.0127204	.0479305	.1271776
Leverage	11635	.6694806	.2270693	.5220802	.7011092	.8367695
ln_sales	11635	17.69332	.1163479	17.59141	17.68808	17.79095
ln_assets	11635	17.40172	.7066612	16.98095	17.38302	17.78243
roe	11634	.0706486	4.98322	.0279349	.09674	.1971695
capital	11635	.0726484	.0970257	.0119541	.0394938	.0934111
liquidity	11635	1.799884	9.484084	1.083552	1.329554	1.86473

Table 1: Summary Statistics of Variables Within 20% Bins Around the Sales Threshold

This table presents detailed summary statistics of key variables for firms that fall within a 20% range around the sales threshold. It includes measures such as mean, median, standard deviation, minimum, and maximum values, providing insights into the financial and operational characteristics of firms near the sales cutoff point.

In order to mitigate potential omitted variable bias, some fixed effects are included in the empirical analysis. For instance, *"nace_2_digit_industry"* represents the industry classification of the firm, based on the NACE 2-digit sector code. This variable allows to account for industry – specific effects, as they may impact the firm performance and subsidy allocation. If these industry-specific characteristics are not controlled for, the analysis could wrongly attribute differences in firm performance or subsidy allocation to other variables rather than to industry factors. (See Wooldridge (2001))

Another potential source of bias may be related to the firm's location, as firms in different regions may experience different economic conditions, which could affect their performance and access to subsidies. Indeed, according to the statistics report made by the Ministry

Around 20% of the 43 million Total assets threshold						
Variable	N	Mean	SD	p25	p50	p75
sub	14576	.0555022	.2289657	0	0	0
ln_amount	14576	.5973662	2.473181	0	0	0
AdjROA	14514	.0114619	.0926268	-.0281683	0	.0404412
firms_age	14576	3.205406	.6997385	2.772589	3.332205	3.663562
ebitda	14514	-.0349944	8.25577	.0374036	.0861891	.1788397
roa	14514	.0751974	.0961391	.0279524	.0608831	.1103772
cash	14460	.0763314	.1109216	.006145	.0314059	.1003106
Leverage	14574	.6173422	.2671573	.4323785	.6465934	.8095887
ln_sales	14576	16.92667	1.399289	16.4687	17.32115	17.79379
ln_assets	14576	17.53911	.1159081	17.43714	17.53221	17.6355
roe	14574	-.0403516	5.182234	.0053716	.0564731	.1461027
capital	14576	.0888298	.1259717	.0129848	.0452719	.1132205
liquidity	14573	284.9891	34028.85	1.046187	1.374068	2.13553

Table 2: Summary Statistics of Variables Within 20% Bins Around the Total Assets Threshold

This table presents detailed summary statistics of key variables for firms that fall within a 20% range around the Total assets threshold. It includes measures such as mean, median, standard deviation, minimum, and maximum values, providing insights into the financial and operational characteristics of firms near the sales cutoff point.

of Firms and made in Italy, the northern area registered a greater number of applications and beneficiaries. (See Ministry of Enterprises and Made in Italy (2017) and Ministry of Enterprises and Made in Italy (2018)). The "Province" variable, derived from the firm's postal code, controls for these regional effects. Without controlling for regional differences, the analysis could mistakenly interpret regional economic advantages as effects of other variables. (See Wooldridge (2001))

4.1.1 Industry distribution

When examining the distribution of the observations across all years from the industry perspective, it is interesting to note that a significant portion of the sample consists of firms in the manufacturing and wholesale trade sectors, followed by the construction industry. Indeed, as shown in Table 4 and 3, this pattern holds even when the sample is restricted to the firms near the specified thresholds. The results regarding the distribution across sectors align with the findings reported by the Ministry of Enterprises and Made in Italy (2017) and Ministry of Enterprises and Made in Italy (2018).

sector	Freq.	Percent	Cum.
ACCOMMODATION AND FOOD SERVICE	121	1.04	1.04
ADMINISTRATIVE AND SUPPORT SERVICE	360	3.09	4.13
AGRICULTURE, FORESTRY AND FISHING	203	1.74	5.88
ARTS, ENTERTAINMENT AND RECREATION	61	0.52	6.40
CONSTRUCTION	351	3.02	9.42
EDUCATION	8	0.07	9.49
ELECTRICITY and GAS SUPPLY	146	1.25	10.74
HUMAN HEALTH AND SOCIAL WORK	183	1.57	12.32
INFORMATION AND COMMUNICATION	309	2.66	14.97
MANUFACTURING	5,137	44.15	59.12
MINING AND QUARRYING	15	0.13	59.25
OTHER SERVICE ACTIVITIES	12	0.10	59.36
REAL ESTATE ACTIVITIES	89	0.76	60.12
SCIENTIFIC AND TECHNICAL ACTIVITIES	318	2.73	62.85
TRANSPORTATION AND STORAGE	524	4.50	67.36
WATER SUPPLY	209	1.80	69.15
WHOLESALE AND RETAIL TRADE	3,589	30.85	100.00
Total	11,635	100.00	

Table 3: Distribution of Firms Across Industries within 20% Bins Around the Total Sales Threshold

This figure displays the distribution of firms categorized by industry over all years, illustrating the concentration and relative representation of each sector within the dataset.

sector	Freq.	Percent	Cum.
ACCOMMODATION AND FOOD SERVICE	375	2.57	2.57
ADMINISTRATIVE AND SUPPORT SERVICE	398	2.73	5.30
AGRICULTURE, FORESTRY AND FISHING	392	2.69	7.99
ARTS, ENTERTAINMENT AND RECREATION	108	0.74	8.73
CONSTRUCTION	1,068	7.33	16.06
EDUCATION	20	0.14	16.20
ELECTRICITY and GAS SUPPLY	279	1.91	18.11
HUMAN HEALTH AND SOCIAL WORK	337	2.31	20.42
INFORMATION AND COMMUNICATION	377	2.59	23.01
MANUFACTURING	6,025	41.34	64.35
MINING AND QUARRYING	73	0.50	64.85
OTHER SERVICE ACTIVITIES	30	0.21	65.05
PUBLIC ADMINISTRATION AND DEFENCE	4	0.03	65.08
REAL ESTATE ACTIVITIES	1,103	7.57	72.65
SCIENTIFIC AND TECHNICAL ACTIVITIES	524	3.59	76.24
TRANSPORTATION AND STORAGE	574	3.94	80.18
WATER SUPPLY	354	2.43	82.61
WHOLESALE AND RETAIL TRADE	2,535	17.39	100.00
Total	14,576	100.00	

Table 4: Distribution of Firms Across Industries within 20% Bins Around the Total Assets Threshold

This figure displays the distribution of firms categorized by industry over all years, illustrating the concentration and relative representation of each sector within the dataset.

4.1.2 Firms' categories

To have a clear overview of the observations, firms are then divided into three categories as defined by European Commission (2003). First, Micro – small, which are the ones that meet either the requirements for a micro or small enterprise, which are a number of employees fewer than 50 and the total assets or total sales below 10 million. Medium, when the firm has a number of employees lower than 250 and either the total assets below 43 million or total sales below 50 million. Lastly, Large for those that do not fall within the above categories.

Examining the distribution in 2015 and 2016, the largest concentration of firms falls under the medium category, being around the 64% - 65%, as shown in Figure 4 and 5. This aligns with the way the dataset was constructed. There are indeed several cases where firms do not respect the criteria of having fewer employees than 50 or having both total assets and total sales exceeding 10 million euros, resulting in their classification as medium firms.

Then micro-small count in 2015 for the 20.82% and in 2016 the 19,12%. Lastly, the large category accounts for 14.96% in 2015 and increases to 16.29% in 2016.

Additionally, there is a small portion of firms classified as large, even though they have a number of employees that falls within the micro-small category. This situation highlights the complexity of firm categorization for grant eligibility, where financial performance can sometimes contradict employee size.

In the regression analysis, the number of employees is excluded as a requirement and several intervals are used to account for these scenarios and to control for such discrepancies.

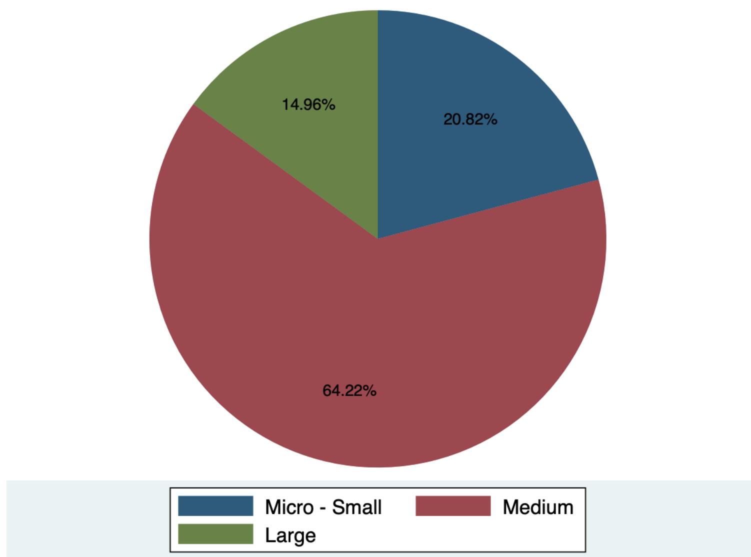

Figure 4: Firm Size Distribution in 2015

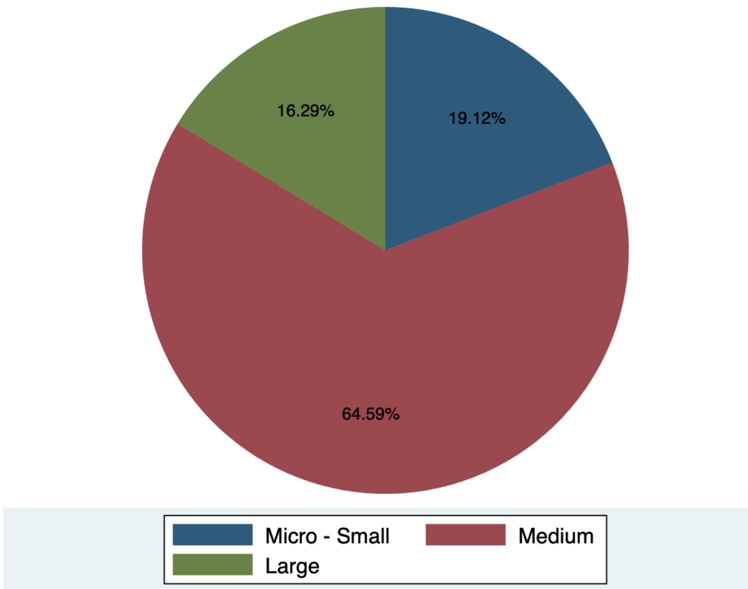

Figure 5: Firm Size Distribution in 2016

4.1.3 Distribution of the beneficiaries

Consistent with the overall distribution of observations across industry sectors, Table 5 shows that the manufacturing sector is the primary beneficiary. This sector benefits significantly from financial support, as it enables firms to innovate and modernize their production processes. Indeed, this finding aligns well with the objectives of the subsidy policy, which aims to provide funding for the firms to acquire new machinery, enhancing thus operational efficiency. Other key sectors that benefit from the subsidies include wholesale trade and construction, which probably used the support to improve their infrastructure and technological capabilities.

Moreover, it is important to note that most observations are not beneficiaries, as they have *"sub"* equal to 0. Then, among the beneficiaries, both in 2015 and 2016 the majority are classified as medium-sized firms, representing approximately 90%, as shown in Table 6 and 7. Micro-small firms count for a small amount of beneficiaries. However, this result is influenced by the methodology employed to select the observations from the Orbis database. Specifically, the selection criteria described allows us to compare firms that are similar, potentially excluding those that consistently fall into the small category.

According to reports from Ministry of Enterprises and Made in Italy (2017) and Ministry of Enterprises and Made in Italy (2018), small enterprises are typically the beneficiaries in terms of the number of firms, although medium-sized firms often receive a larger share of the grant amounts. This dynamic makes the research question particularly relevant, as it highlights the differing impacts of the subsidy program across firm sizes.

Lastly, a few beneficiaries are categorized as large firms. This is due to the timing mismatch between the application and the financial statements used. Indeed, it is nearly impossible to determine whether a firm applied for the subsidy in 2017 or 2018 using financial data from 2015 or 2016.

sector	sub 0	1	Total
ACCOMMODATION AND FOOD SERVICE	2.10	0.07	2.17
ADMINISTRATIVE AND SUPPORT SERVICE	3.17	0.05	3.22
AGRICULTURE, FORESTRY AND FISHING	2.12	0.01	2.13
ARTS, ENTERTAINMENT AND RECREATION	0.70	0.01	0.70
CONSTRUCTION	6.30	0.46	6.76
EDUCATION	0.10		0.10
ELECTRICITY and GAS SUPPLY	1.72	0.01	1.73
HUMAN HEALTH AND SOCIAL WORK	1.85	0.07	1.92
INFORMATION AND COMMUNICATION	2.79	0.03	2.82
MANUFACTURING	33.43	4.13	37.56
MINING AND QUARRYING	0.32	0.06	0.38
OTHER SERVICE ACTIVITIES	0.21		0.21
PUBLIC ADMINISTRATION AND DEFENCE	0.01		0.01
REAL ESTATE ACTIVITIES	5.61	0.03	5.64
SCIENTIFIC AND TECHNICAL ACTIVITIES	3.38	0.03	3.42
TRANSPORTATION AND STORAGE	4.71	0.25	4.96
WATER SUPPLY	2.24	0.12	2.37
WHOLESALE AND RETAIL TRADE	22.94	0.97	23.90
Total	93.70	6.30	100.00

Table 5: Sectoral Distribution of Subsidy Beneficiaries as percentages

This figure illustrates the percent distribution of subsidy beneficiaries across different sectors for the years 2015 and 2016 distinguishing between subsidy beneficiaries and non-beneficiaries.

	sub		
	0	1	Total
firm_size			
Micro - small	20.18	0.64	20.82
Medium	58.62	5.60	64.22
Large	14.91	0.05	14.96
Total	93.70	6.30	100.00

Table 6: Firm Size Distribution in 2015 as percentages by Subsidy Status

These figures shows the percentages of firm sizes for the years 2015, distinguishing between subsidy beneficiaries and non-beneficiaries.

	sub		
	0	1	Total
firm_size			
Micro - small	18.67	0.45	19.12
Medium	58.79	5.80	64.59
Large	16.25	0.04	16.29
Total	93.70	6.30	100.00

Table 7: Firm Size Distribution in 2016 as percentages by Subsidy Status

These figures shows the percentages of firm sizes for the years 2016, distinguishing between subsidy beneficiaries and non-beneficiaries.

5 Evidence of *bunching*

In examining how to identify bunching, the academic literature on taxation and non-taxation policies refers to the conceptual framework developed by Chetty (2012) and Kleven and Waseem (2013). These studies distinguish between "kinks" and "notches" in policy design. More specifically, a "kink" denotes a change in the slope of the individuals' choice set while the second to changes to discontinuities in the choice set.

Given that the New Sabatini Law establishes two thresholds, such that the firm is eligible only if it falls below, the notches framework is more appropriate in this context. Firms just above the threshold face an all-or-nothing decision, meaning that being above is a strictly dominated decision compared to the benefits of being in the below area. Indeed, as highlighted in the literature, such a notch may induce firms, that would otherwise be above the threshold, to adjust their behavior to meet the requirements and thus qualify for the grants. The result is an excess bunching mass on the lower side of the cutoff point, as compared to the region directly above, where choices are strictly dominated. (See Kleven and Waseem (2013)).

It is then important to recall that the 43-million-Total assets and 50-million-Sales thresholds are unique, which means specifically used to qualify for subsidies. The consequence is that irregular patterns in the distribution, such as spikes, likely indicate that firms strategically adjusted their metrics to become eligible for grants.

Looking at Figure 6, 7, 8, 9, 10 and 11, the total assets and sales of the year 2014 can be used as benchmarks, as a change in the New Sabatini program was announced in January 2015 and enacted into law in March 2015. Thus, in 2014 firms had no specific incentive to jump below the thresholds besides the general advantages of being classified as a small-medium firm, such as eligibility for other subsidies or tax benefits with the same requirements. Indeed, the distribution of 2014 shows no sign of excess mass before the cut-off points.

During 2016 there was a boost of applications for the new Sabatini program and, after that, the Italian government decided to extend the policy for 2017 and 2018, while increasing the amount of the available resources.

Firms that benefited from the subsidy in 2016 did not have sufficient time to adjust their financial statements, considering that probably they were presenting the financial statements of 2014. However, the scenario was different for firms applying in 2017, as they were likely presenting financial statements from either 2015 or 2016, thus having time to adjust accordingly. For instance, when considering the firms near the same thresholds but in 2015, the year of the announcement, there is an evident concentration of enterprises just below the 50-million- sales notch. This excess mass can be interpreted as bunching, particularly given the sharp drop in the number of firms immediately above the threshold. (See (Kleven and Waseem (2013)), (Chetty (2012)) and (Saez (2010)).

Moreover, since meeting either the sales or assets requirement is sufficient to qualify for the subsidy, two key observations arise. First, the largest concentration of sales firms is right below 50 million, signalling that probably these firms would likely have been above the threshold in a counterfactual scenario without the policy change. Notably, the distribution starts to increase several bins before the notch, which is logical given that management strategies for size reduction may not be entirely precise. (See Bernard et al. (2018)). Second, since firms are not required to reduce both sales and assets to become eligible, this could explain the absence of a significant shift around the assets' threshold in 2015.

Examining 2016, firms had more time to adapt to the requirements following the announcement in 2015. Sales do not show an abnormal pattern around the cut-off point, instead a steady trend around the threshold. However, since the sample includes the same unique firms over multiple years, the bunchers could have already changed in 2015. There is, then, clear evidence of an abnormal concentration just before the 43-million assets at the notch, followed by a notable drop immediately after. Again, this excess mass density can be interpreted as a bunching pattern. (See Kleven and Waseem (2013)).

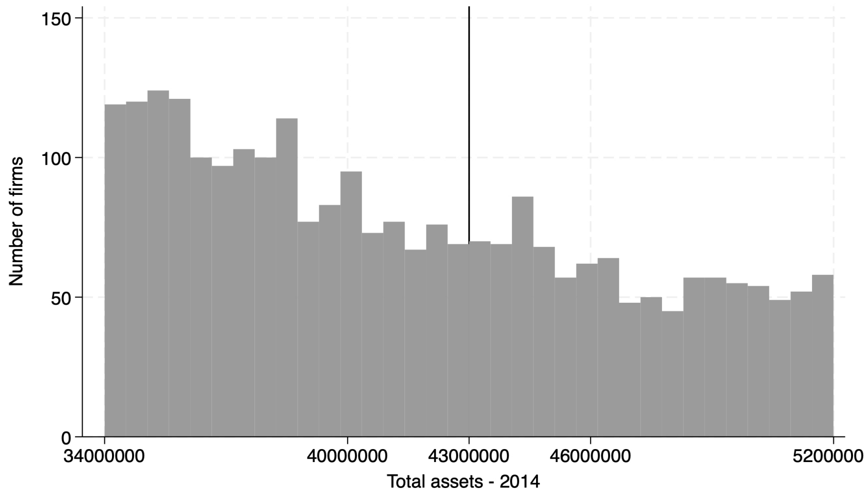

Figure 6: Distribution of Total assets in 2014

This figure presents the distribution of Total assets in 2014. The vertical line represents the 43 million Total assets threshold.

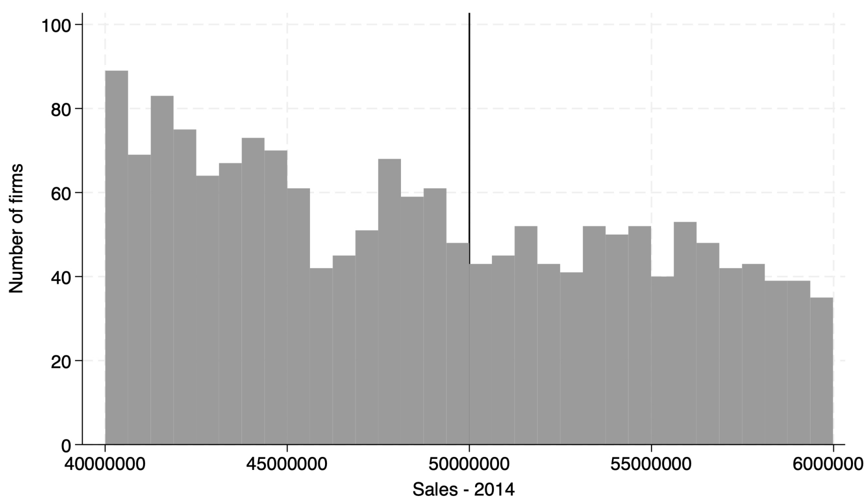

Figure 7: Distribution of Total sales in 2014

This figure presents the distribution of Total sales in 2014. The vertical line represents the 50 million Total sales threshold.

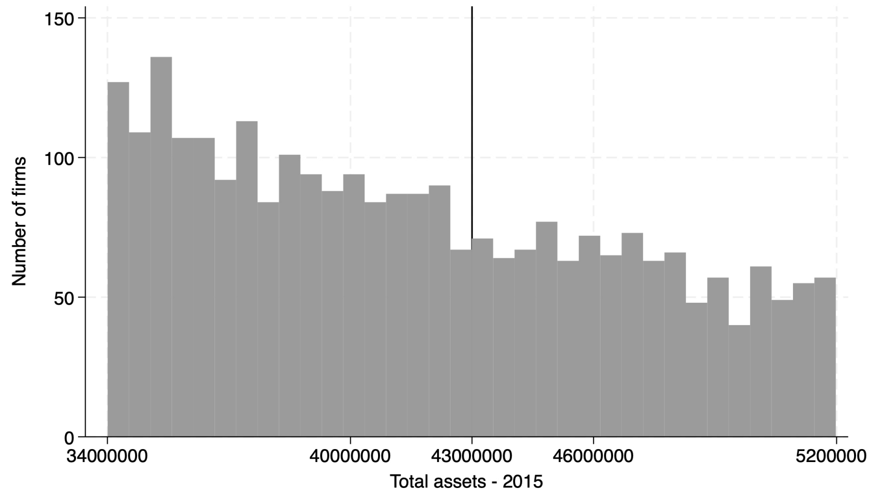

Figure 8: Distribution of Total assets in 2015

This figure presents the distribution of Total assets in 2015. The vertical line represents the 43 million Total assets threshold.

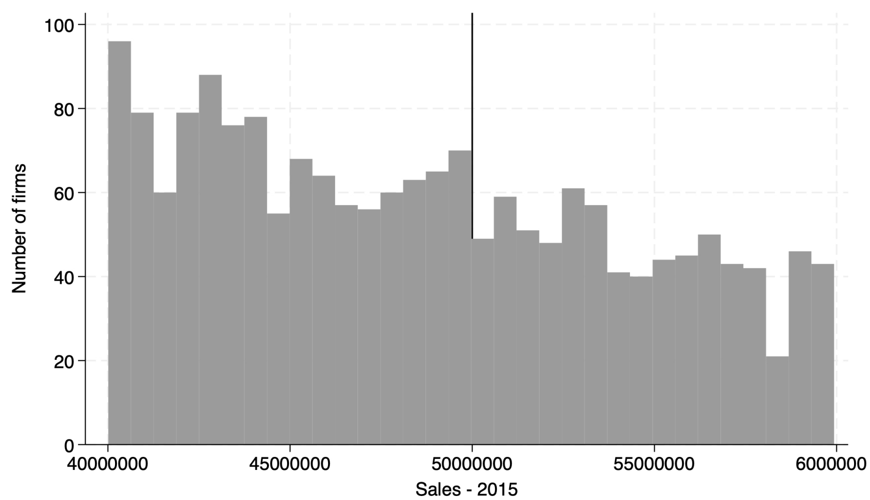

Figure 9: Distribution of Total sales in 2015

This figure presents the distribution of Total sales in 2015. The vertical line represents the 50 million Total sales threshold.

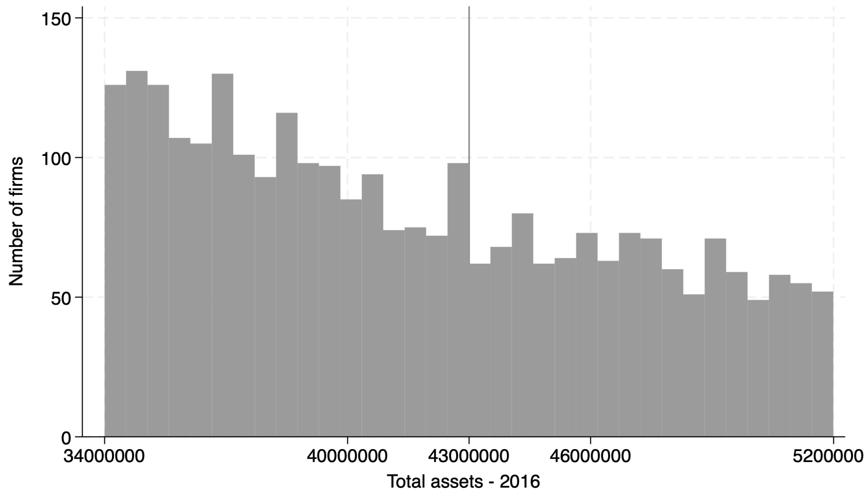

Figure 10: Distribution of Total assets in 2016

This figure presents the distribution of Total assets in 2016. The vertical line represents the 43 million Total assets threshold.

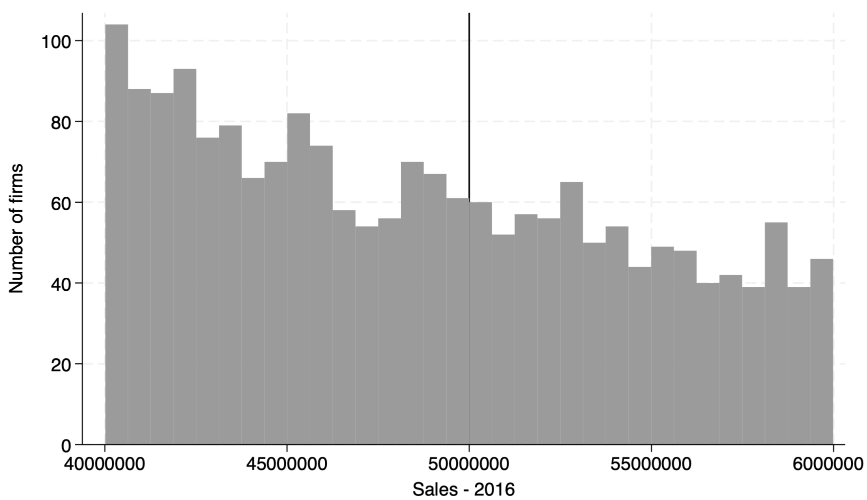

Figure 11: Distribution of Total sales in 2016

This figure presents the distribution of Total sales in 2016. The vertical line represents the 50 million Total sales threshold.

5.1 Identification and Estimation of *bunching*

In terms of estimation, the bunching mass can be conceptualized as the difference between the observed mass of firms near the threshold and the counterfactual mass that would exist in the absence of the policy. This framework has been employed in the literature to determine the structural elasticities that drive individuals' behavioral responses. More in detail, it consists of constructing the counterfactual distribution of the variable of interest, such as without the notch or kink, and estimating it by excluding observations around the threshold. The range is chosen by visual inspections, where the excess mass starts. Then, the extent of bunching is measured by comparing the expected distribution density with the observed one. This difference captures the behavioral responses of firms that adjust their finances to fall below the cutoff point. The basic form of the equation to estimate bunching can be expressed as:

$$\hat{B} = \sum_{j=L}^{0} (n_j - \hat{n}_j) \tag{1}$$

Where $\hat{B}$ measures the excess bunching, n_j is the observed distribution around the eligibility cutoff, while $\hat{n}_j$ is the estimated counterfactual distribution. (See Kleven (2016), Di Marzio et al. (2024)).

As the research question in this thesis aims to determine whether there is a causal relationship between the New Sabatini Law and the strategic behavior of firms seeking to qualify for the policy, the traditional framework used to estimate bunching was adapted to a different identification strategy. Indeed, a specific definition for the manipulator firms is proposed to retrieve the excess mass, which supports the graphic evidence of bunching, but based on the comparison of the distribution around the thresholds for two years. It is important to clarify that here "manipulation" refers to financial adjustments within the boundaries of the law. Moreover, the employees' requirement is not taken into account, as in the sample it is unusual that a firm does not fall into the small-medium enterprises category because of a larger number of employees. Thus, the key variables are the management of total assets or total sales.

More in detail, in 2015 there was the announcement of a policy change, applications opened in 2016 and then extended to 2017. In addition, to have a clearer picture of the firms' behavior, there is the assumption that there are optimization frictions. So not all firms engage in bunching immediately after the announcement, even when they have an incentive to do so, because of adjustment costs or incomplete information. Therefore, firms may adjust either in 2015 or 2016. (See Kleven and Waseem (2013) and Gunny (2010)).

Taking into account this time frame and the fact that it is enough to meet the criteria at the time of the application, a manipulative behavior is defined as follows:

A manipulative firm is one that in 2014 was not eligible for the subsidy, thus not compliant, because it exceeded both the set thresholds. Specifically, the firms had both total assets greater than 43 million and sales larger than 50 million. Subsequently, the firm reduced the size in 2015, falling below either the 43 million total assets or 50 million total sales cutoff points. Considering the possibility that the adjustment is not immediate, the same definition is applied when comparing 2015 and 2016. Lastly, if the firm is identified as a buncher in 2015, it will be considered as it again in 2016, since it is not possible to determine whether the firm presented the balance sheet of 2015 or 2016 for the application.

The reference variable for bunching along the analysis is *"below"*, which is a dummy constructed based on the above description, such as if the firm changed in 2015 or in 2016 with the respect to the previous year. Recalling that if the firm is bunching in 2015, the binary variable *"below"* equals 1 also in 2016. In the sample there are 454 observations identified as bunching between 2015 and 2016 (see Table 8). The number decreases to 211 (see Table 10) and 185 (see Table 9) when considering only the observations within the 20% intervals around the thresholds.

below	Freq.	Percent	Cum.
0	22,540	98.03	98.03
1	454	1.97	100.00
Total	22,994	100.00	

Table 8: Distribution of firms identified as *bunching* firms in 2015 and 2016

below	Freq.	Percent	Cum.
0	4,522	96.07	96.07
1	185	3.93	100.00
Total	4,707	100.00	

Table 9: Distribution of firms identified as *bunching* within the 20% bins around the 43 million Total assets threshold in 2015 and 2016

below	Freq.	Percent	Cum.
0	3,478	94.28	94.28
1	211	5.72	100.00
Total	3,689	100.00	

Table 10: Distribution of firms identified as *bunching* within the 20% bins around the 50 million sales threshold in 2015 and 2016

5.2 A deeper insight

It is useful to disentangle the patterns that characterizes the variable *"below"*:

a. 2014 vs 2015: By comparing these years, the purpose is to observe the immediate response after the announcement of the policy change in 2015. Considering that from the non-parametric analysis there is evidence of a jump in sales, it is important to understand if the announcement had such a big impact that incentivized firms to adjust suddenly or not. In this case, the financial data of 2014 are compared with the one of 2015, such that, a bunching behaviour is the change of collocation in the distribution from being above in 2014 to below in 2015.

A total of 160 firms meet the definition of bunching in this period (see Table 11). Among them, 59 firms adjusted their total assets, while 113 enterprises their sales. The result is consistent with the non-parametric evidence, which shows significant movement in sales. When restricting the sample to the 20% intervals near the specific points, the number of buncher firms drops. Precisely, the number of bunchers decrease to 82 around the sales cut-off point, counting for 71 firms adjusting their sales (see Table 11), and to 65 around the total assets cut-off point, with 46 firms managing their total assets (see Table 11).

While the interval specification accounts for the fact that some firms may not fall precisely near the threshold, the reduction in the number of firms classified as manipulators suggests that some of these may not be located below for opportunistic reasons. Thereby, this highlights the importance of having an appropriate window of analysis.

b. 2015 vs 2016: The objective is to determine whether new firms started to adjust in 2016, probably related to the fact that the policy change was extended for another two years. In this case, enterprises had more time to adjust to the set criteria. Here, those firms that already jumped in 2015 are not taken into consideration. As shown in the Table 12, there are 134 enterprises categorized as non-compliant, 63 when restricting the sample around the 20% bins of the sales threshold and the assets one.

Interestingly, although the Figure 10 has a spike in the total assets of 2016, it seems that

bunching 2015												
					20% bins around the 43 million-total assets threshold				20% bins around the 50 million-sales threshold			
bunching 2015:	0	1	percentage	Total	0	1	percentage	Total	0	1	percentage	Total
bunching sales = 0	11,337	47	29.38%	11,384	2,244	37	56.92%	2,281	1,691	11	13.41%	1,702
bunching sales = 1	0	113	70.63%	113	0	28	43.08%	28	0	71	86.59%	71
bunching assets = 0	11,337	101	63.13%	11,438	2,244	19	29.23%	2,263	1,691	65	79.27%	1,756
bunching assets = 1	0	59	36.88%	59	0	46	70.77%	46	0	17	20.73%	17
Total (for bunching 2015):	11,337	160		11,497	2,244	65		2,309	1,691	82		1,773

Table 11: Distribution of firms identified as bunching in 2015

This figure shows the distribution of firms identified as bunching by comparing the financial statements of 2014 and 2015. Percentages are calculated using the total number of firms identified as bunching in 2015 as the denominator.

the phenomenon of manipulation is more concentrated near the sales threshold rather than the total assets. Indeed, there are 93 firms that managed their sales and 55 changed their total assets. However, when shrinking to the narrower range of 20%, the number of sales adjustments drops to 55, while total assets decrease slightly less, to 44, reflecting the evident spike observed in Table 12.

bunching 2016												
					20% bins around the 43 million-total assets threshold				20% bins around the 50 million-sales threshold			
bunching 2016:	0	1	percentage	Total	0	1	percentage	Total	0	1	percentage	Total
bunching sales = 0	11,363	41	30.60%	11,404	2,335	35	55.56%	2,370	1,853	8	12.70%	1,861
bunching sales = 1	0	93	69.40%	93	0	28	44.44%	28	0	55	87.30%	55
bunching assets = 0	11,363	79	58.96%	11,442	2,335	19	30.16%	2,354	1,853	48	76.19%	1,901
bunching assets = 1	0	55	41.04%	55	0	44	69.84%	44	0	15	23.81%	15
Total (for bunching 2016)	11,363	134		11,497	2,335	63		2,398	1,853	63		1,916

Table 12: Distribution of firms identified as bunching in 2016

This figure shows the distribution of firms identified as bunching by comparing the financial statements of 2015 and 2016. Percentages are calculated using the total number of firms identified as bunching in 2016 as the denominator.

5.3 Beneficiaries: *naturally eligible* vs *opportunistic bunching*

Considering an overall of 11,497 unique observations in 2016, 724 firms obtained the New Sabatini subsidy either in 2017 and/or in 2018, but for only 14 firms the variable *"below"* equals 1 (see Table 13). Analyzing more in detail the distribution of beneficiaries within the 20% bins around the thresholds, the frequency of *"below"* further shrinks.

Given the identification of bunching, firms can be then divided into three groups for a clear description. First there are the *Naturally eligible*, those firms that are below either one of the two thresholds comparing 2014 to 2015 and 2015 to 2016. These firms already meet the eligibility criteria and are considered compliant.

Then, *Opportunistic eligible*, these are firms that were non-compliant in 2014 but managed to collocate below in 2015, or were above in 2015 but adjusted to fall below in 2016. This category is constructed based on the variable *below*.

Lastly, *Not eligible*, the firms that remained above the thresholds in both 2015 and 2016.

Examining the distribution across the three categories of - *naturally eligible*, *bunching*

	sub		
below	0	1	Total
0	21,106	1,434	22,540
1	440	14	454
Total	21,546	1,448	22,994

Table 13: Distribution of firms in 2015 and 2016 identified as 'bunching' based on whether they received the subsidy

and *not eligible* -, depending on the chosen threshold, the *Naturally eligible* category includes mostly of the total population. This group includes enterprises that were already eligible in both 2014 and 2015, as shown in Tables 14 and 15. Indeed, these firms were the primary beneficiaries of the New Sabatini subsidy, with only a small number of beneficiaries identified as *opportunistic eligible*, thus with *"below"* equal to 1.

In addition, there is the fact that also a few of those not eligible received the subsidy, likely because they presented the financial statements from the previous year that met the requirements.

Therefore, we can state that even though there is evidence of bunching, the beneficiaries are mainly firms *Naturally eligible*, as already noted.

	sub								
				Around the 20% of the 43 million total assets threshold			Around the 20% of the 50 million sales threshold		
firm_status_2015	0	1	Total	0	1	Total	0	1	Total
Naturally eligible	8,944	713	9,657	1,692	110	1,802	1,161	54	1,215
Opportunistic eligible	117	5	122	46	3	49	53	4	57
Not Eligible	1,712	6	1,718	454	4	458	497	4	501
Total	10,773	724	11,497	2,192	117	2,309	1,711	62	1,773

Table 14: Distribution of firms in 2015 across the categories: naturally eligible, opportunistic eligible, and not eligible

This table shows the distribution of firms in 2015 according to the categories: naturally eligible, opportunistic eligible, and not eligible. First all the firms are considered, then only those in the 20% around the thresholds.

	sub								
				Around the 20% of the 43 million total assets threshold			Around the 20% of the 50 million sales threshold		
firm_status_2016	0	1	Total	0	1	Total	0	1	Total
Naturally eligible	8,722	710	9,432	1,754	106	1,860	1,217	66	1,283
Opportunistic eligible	188	9	197	76	8	84	85	4	89
Not Eligible	1,863	5	1,868	450	4	454	542	2	544
Total	10,773	724	11,497	2,280	118	2,398	1,844	72	1,916

Table 15: Distribution of firms in 2016 across the categories: naturally eligible, opportunistic eligible, and not eligible.

This table shows the distribution of firms in 2016 according to the categories: naturally eligible, opportunistic eligible, and not eligible. First all the firms are considered, then only those in the 20% around the thresholds

6 Empirical strategy

6.1 The Model

6.1.1 Logit model:

The first model employed in the thesis to test hypothesis 1 is a logit model, which is estimated using the maximum likelihood. This technique is particularly useful for empirical analysis where the dependent variable is binary, such that it takes values of 1 or 0. The logit model is based on the cumulative logistic distribution, which ensures that the predicted value of the dependent variable is constrained between 0 and 1, making it more suitable for binary outcomes:

The probability of $D_i = 1$ is given by:

$$\Pr(D_i = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon)}}$$

Rearranged into a log-odds ratio:

$$\ln\left(\frac{D_i}{1 - D_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon$$

To obtain:

$$L : \Pr(D_i = 1) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon$$

$$\text{where } \epsilon \sim N\left(\tfrac{1}{NP_i(1-P_i)}\right).$$

In a logit model, the coefficients β_1 and β_2 represent the change in the log-odds of the dependent variable for a one-unit change in the corresponding independent variables X_{1i} and X_{2i}. Although the signs of the coefficient in a logit model often align with those of a linear probability model, the interpretation is quite different. Indeed, the coefficient from the logit model represents logs-odd and not probabilities, given the fact that the relationship between the independent variables and the probability of the outcome is non-linear. (See

Studenmund (2014)) That is why, it is necessary to calculate marginal effects, which show how a unit change in the independent variable affects the probability of the outcome, holding the other variables constant. In Stata the margin command directly computes the marginal effects, making them directly interpretable in terms of probabilities.

6.1.2 Difference-in-Differences:

To assess the effect of bunching on the firm's long-term performance, a Difference-in-Differences (DiD) model was used. This model allows us to compare outcomes between treated and not treated groups before and after the intervention, estimating the average effect of the treatment. Given two - period setting, where t = 0 denotes the period before the treatment and t = 1 the period after, DiD estimates the treatment effect by comparing changes in outcomes across groups.

The difference-in-differences (DD) estimator is defined as:

$$\mathrm{DD} = \mathbb{E}(Y_1^T - Y_0^T \mid T_1 = 1) - \mathbb{E}(Y_1^C - Y_0^C \mid T_1 = 0)$$

where Y^C and Y^T are respectively the outcomes of the control and treated groups in time t. Moreover, $T_1 = 1$ specifies the presence of the treatment at time $t = 1$, while $T_1 = 0$ defines the untreated.

The corresponding regression equation used to estimate the treatment effect is:

$$Y_{it} = \alpha + \beta T_{i1} t + \rho T_{i1} t + \gamma t + \epsilon_{it}$$

Where the coefficient β is the interaction term, such that it captures the difference over time between the treated and control groups. In other words, β computes the effect of being in the treated group T_{i1} and in the post treatment period ($t = 1$).

The term ρ estimates the effect of being in the treated group, compared to the control one, which means controlling for the treated time-invariant characteristics.

Lastly, γ accounts for time specific effects that affect the two groups equally. This dummy equals 1 in the after-treatment period and controls for the common time trend. (See Khandker et al. (2009)).

In order for the DID model to yield unbiased estimates of the treatment effect, some assumptions must be true. The first one is the common trend hypothesis, which requires the error term to be uncorrelated with the other variables. That means, in the absence of treatment, the treated and control groups are expected to follow the same trend over time. Then, there should be no spillover effects or anticipations, such that the treated group should not anticipate the treatment, and the treatment should not affect the outcomes of the control group. Lastly, the linearity and additivity assumptions, which means that the characteristics of each group are constant over time and the variation of the outcomes is common across groups. (See Khandker et al. (2009)).

6.2 Models Specifications

Logit model: Given the structure of the dataset, with a large number of firms but limited within-firm variability over time, a logistic regression model is used to estimate the likelihood of receiving a subsidy. The objective of the model is first to capture if the probability of obtaining the New Sabatini subsidy between 2017 and 2018 is influenced by firms' strategic behaviour. Specifically the question is whether *opportunistic eligible*, those that managed their finances either in 2015 or 2016, have a greater likelihood of obtaining the grant. For this reason, a logit model is employed, focusing on the 18%, 20% and 22% left bins around the sales and assets threshold, to ensure robustness of the results. This approach allows for the comparison between *opportunistic eligible*, those that adjusted their financials, with *naturally eligible* firms, those always below the cut-off points.

Firstly, *"sub"* is defined as:

$$D_i = \text{sub}_f = \begin{cases} 1 & \text{if the firm obtained the subsidy} \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the probability of receiving the subsidy is given by:

$$\Pr(\text{sub}_{f,t+1} = 1) = \beta \cdot \text{below}_{f,t} + \delta \cdot \text{controls}_{f,t} + \gamma \cdot \text{sector}_{f,t} + \theta \cdot \text{province}_{f,t} + \varepsilon_{f,t} \qquad (2)$$

where sub_{t+1} is a dummy variable that equals 1 if the firm obtained the New Sabatini subsidy in 2017 and/or 2018, and 0 otherwise.

Below is a dummy variable that equals 1 if the firms manipulated their financial to fall below the threshold in 2015 or 2016, and 0 otherwise. There are then the control variables, as explained in the previous sections, which include firm characteristics, lagged to match the year of bunching, such as "firm_age", "ROA", "cash holdings", "leverage", "ROE", the logarithm of sales and assets, "liquidity" and "capital".

Furthermore, fixed effects for sector - year and province - year are included to control for unobserved heterogeneity across industries and location that might bias the results, providing in this way a more accurate estimate of the behavioral change effect.

Lastly, the errors $\varepsilon_{f,t}$ are clustered at the firm level to account for intra-firm correlation and heteroscedasticity, ensuring then more robust standard errors while addressing issues of potential serial correlation within firms.

The coefficient of interest is β, which measures whether *opportunistic eligible* – non-compliant - have a greater likelihood of obtaining the subsidy compared to the *naturally eligible* firms - compliant.

OLS regression: Given the limited within-firm variation across the two years of data, a pooled OLS model with clustered standard errors is employed. The choice of a pooled OLS model allows us to exploit both the between-firm and within-firm variation in the data.

While, clustering standard errors ensures to account for the fact that observations are not independent across time periods.

More in detail, an important assumption in pooled OLS is that unobserved firm-specific characteristics are uncorrelated with the independent variable. To mitigate the omitted variable bias, firm fixed effects should be included. However, while they would be useful to control the unobserved firm characteristics, the limited firm variation would lead to imprecise estimates. Therefore, to address the potential omitted variables bias, the regression is conducted within multiple narrow intervals, ensuring that firms around the thresholds are likely to be homogenous. This approach reduces the impact of unobserved firm characteristics that could otherwise bias the result. (See Wooldridge (2001)).

A second important assumption is that the error terms across different periods are uncorrelated. However, since in the sample there are repeated observations of the same firms, the error terms across time may likely be correlated. That is why clustering standards error at the firm level is crucial. By doing so, the model adjusts for potential serial correlation within firms, while focusing on how firm characteristics and financial manipulation influence the grant amount. (See Wooldridge (2001)).

More in detail, this approach allows us to estimate the relationship between firm characteristics and the grant amount, while accounting for the fact that the same firms are observed in multiple years:

$$Y_{t+1} = \beta \cdot \text{below}_{f,t} + \delta \cdot \text{controls}_{f,t} + \gamma \cdot \text{sector}_{f,t} + \theta \cdot \text{province}_{f,t} + \varepsilon_{f,t} \tag{3}$$

Where Y_{t+1} represents the natural logarithm of 1 plus the grant amount obtained by the firm in 2017 and/or 2018. *Below* is again a dummy variable that equals 1 for the firms identified as manipulators of their financials in either 2015 or 2016 and 0 otherwise.

The model includes a set of control variables lagged to the same year of *Below*, such as ”firm_age”, ”ROA”, ”cash holdings”, ”leverage”, ”ROE”, the logarithm of sales and assets, ”liquidity” and ”capital”.

Additionally, sector - year and province - year fixed effects are incorporated to control for unobserved heterogeneity across industries and regions. As before, the errors $\varepsilon_{f,t}$ are clustered at the firm level to account for potential correlation within firms over time and ensure robust standard errors.

In the same manner as with the logit model, firms within the 18%, 20% and 22% in the left bins around the 50-million-sales and 43-million-total assets thresholds are considered for the OLS regressions, allowing for a comparison between similar firms but defined *opportunistic eligible* or *naturally eligible*.

The coefficient of interest is β, which captures the causal effect of financial manipulation on the grant amount obtained by firms. Specifically, it measures whether firms that strategically adjusted their finances to fall below the subsidy cut-off point received a larger subsidy amount compared to those constantly eligible. If the coefficient is significant and positive, this would suggest that firms which actively sacrificed growth in some ways secured a larger amount. This would imply that changes in the New Sabatini program may have incentivized such behaviour.

Difference-in-Differences: Following the above specification, an Ordinary Least Squares (OLS) model was used to estimate the effect of bunching firms performance, measured by Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA):

$$\text{EBITDA}_t \text{ or } \text{ADJROA}_t = \alpha + \beta \cdot \text{did}_{i1} + \delta \cdot \text{controls}_{f,t} + \gamma \cdot \text{sector}_{f,t} + \theta \cdot \text{province}_{f,t} + \varepsilon_{f,t} \quad (4)$$

The dependent variable is defined by two measures of performance: *"EBITDA*, calculated as EBITDA scaled by sales, and Adjusted ROA (*"ADJROA"*), which is constructed by adjusting each firm's ROA relative to the industry median ROA for that year and sector. (See Gunny (2010)).

Then, *"did"* captures the effect of bunching behaviour on firm performance. Specifically, it is implemented through two interaction terms: *did_a* and *did_s*. Precisely, *did_a* represents bunching behaviour specifically associated with the total assets. It is defined as the interaction between a dummy that identifies firms as engaging in asset-based bunching in 2015 or 2016, and a post-treatment variable that equals 1 in all years from 2017 onward, 0 otherwise.

The dummy *did_s* similarly captures bunching behaviour related to total sales. It is defined as the interaction between a dummy that identifies sales-based bunching in 2015 or 2016 and the post-treatment indicator for 2017 onward.

Together, *did_a* and *did_s* allow for the separate analysis of asset-based and sales-based bunching effects, providing insight into how different size management strategies impact firm performance after the subsidy policy takes effect. This distinction highlights whether the specific type of bunching behaviour (assets or sales) is more closely associated with changes in *"EBITDA"* or *"ADJROA"*.

Moreover, control variables are included to account for firm-specific characteristics that could influence *"EBITDA"* or *"ADJROA"* independently of bunching behavior. These variables include "firm_age", "ROA", "cash holdings", "leverage", "ROE", the logarithm of sales and assets, "liquidity" and "capital". These controls help address firm-level heterogeneity and isolate the effect of bunching on performance. In addition, fixed effects are included for each sector - year combination as well as province – year combination. These ensure to control for sector - specific trends that change over time and regional condition that may impact the performance.

Lastly, the error term is clustered at the firm level to account for the within-firm correlation over time.

This analysis is restricted to firms with *sub = 1*, representing the beneficiaries of the New Sabatini. By focusing on these firms, the analysis directly accounts for the effect of the subsidy. Additionally, this restriction targets firms that more likely changed for opportunistic reasons, thereby comparing bunching and non bunching. In addition, the analysis focuses on firms within a 20% range around the subsidy thresholds, specifically in terms of total assets or sales. This range is selected to capture, again, firms that are most likely managed opportunistically in response to the subsidy eligibility criteria.

The coefficient of interest is β, as it captures the interaction of being a bunching firm and in the post-treatment period (2017 onward). More in detail, it captures the average effect of being a bunching firm on EBITDA or ADJROA in the post-2017 period, isolating any potential impact of size management strategies. If the coefficient β was negative, it would suggest that bunching behavior is associated with a reduction in EBITDA or ADJROA, potentially indicating that firms engaging in size management face performance penalties, probably due to inefficiencies or opportunistic behaviors. (See Gunny (2010)).

On the contrary, a positive β would indicate that bunching firms are associated with better performance outcomes, suggesting that size management may yield efficiency.

6.3 Main Results

Logit model: The results of equation 2, with the dummy *"sub"* as dependent variable, are presented in Table 16, with the standard errors in parenthesis. As explained, the coefficient represents changes in log odds, consequently in order to interpret the magnitude of the effect it is necessary to calculate the marginal effects, which provide the direct change in probabilities of receiving the subsidy. However, the sign is directly interpretable, such that a significant and positive coefficient would imply that opportunistic eligible have a greater likelihood of receiving the subsidy compared to the *naturally eligible* counterparts.

In columns (1) to (3) of Table 16, the results correspond to the 43-million total assets threshold, using bandwidths of 18%, 20% and 22% only to the left side of the threshold.

Similarly, in columns (4) to (6) the coefficients refer to the 50 million sales thresholds, using the same bandwidths. By focusing on the left side of the threshold, the analysis compares *naturally eligible* with those that may have become eligible through opportunistic financial behavior. In addition, variables are added to enrich the model as well as fixed effects, ensuring the results are not biased by these factors.

The coefficient of interest, *below*, which identifies firms classified as manipulators, is not statistically significant across any of the specified bandwidths and at any confidence interval, for this reason the marginal effects were not computed.

The lack of statistical significance suggests that behavioral changes observed in firms, such as managing their size to become eligible, are not associated with the probability of obtaining the New Sabatini. Therefore, firms that were initially above but later fell below either of the two thresholds do not appear to benefit more from the grant allocation process than those firms that were consistently classified as small-medium enterprises.

OLS regressions: Below are presented the results from equation 3, such as derived from pooled Ordinary least square regressions run across different bandwidths, with controls for firm characteristics, industry, and regional fixed effects.

From columns (1) to (3) of Table 17, the coefficients refer to a subsample below the 43-million total assets threshold, while from columns (4) to (6) represent the subsample below the 50-million total sales threshold. The standard errors are reported in brackets and are clustered at the firm level to account for repeated observations of the same firms over time.

Overall, the results indicate that there is no statistically significant evidence that firms classified as *opportunistic eligible* received larger grant amounts compared to *naturally eligible*. Although the coefficients on the *"below"* variable are generally positive, the large standard errors suggest that such effect is not significant.

From one hand, these findings imply that, even though the enterprises seemed to have changed in some ways their financial situation, this did not translate into receiving larger amount. On the other hand, from a policy perspective, the New Sabatini program did not not seem to provide strong incentives for firms to manipulate their financial statements. If firms believed that significant financial gains could be made by manipulating their financials, the expectations were both a higher probability of receiving grants and larger amounts. Therefore, this subsidy was not the driver of the spikes seen in the non-parametric evidence. However, this result aligns with the fact that the main beneficiaries of the subsidy are the small and micro enterprises, which are *naturally eligible*.

Difference-in-Differences: Columns (1) to (3) of Table 18 report the coefficients for *did_a* from equation 4, which captures the effect of asset-based bunching in 2015 and 2016 on

"EBITDA" in the years after 2017, focusing on firms within a 20% range around the assets threshold and limited to subsidy beneficiaries (*sub = 1*).

Initially, the coefficient was significant and negative, indicating a potential negative impact of asset-based bunching on long-term *"EBITDA"*. However, this result is not robust when covariates and fixed effects are added. This suggests that once we account for firm-specific characteristics and fixed effects, asset-based bunching in 2015 and 2016 does not significantly impact *"EBITDA"* in the long term.

A similar conclusion applies to columns (4) to (6) of Table 18, where *did_s* captures sales-based bunching. In this case, reducing sales to fall below the eligibility threshold in 2015 and 2016 does not show a long-term effect on *"EBITDA"*. This outcome remains consistent even with the inclusion of covariates and fixed effects, suggesting that sales-based bunching does not have a persistent impact on firm performance.

To ensure the robustness of these findings, an additional regression was conducted with Adjusted ROA (ADJROA) as the dependent variable, following equation 4, again limited to subsidy beneficiaries within a 20% range around the thresholds.

Columns (1) to (3) of Table 19 display the results for *did_a*. While the coefficient was initially highly significant, this significance drops once sector-level fixed effects are added, suggesting that the initial significance was likely influenced by unobserved sectoral differences rather than a true long-term effect of asset-based bunching.

In columns (4) to (6) of Table 19, *did_s* consistently shows no significant relationship with *"ADJROA"*. This lack of significance is stable across models, even with the inclusion of control variables and fixed effects for sector and province-year, reinforcing the conclusion that sales-based bunching has no long-term impact on the firm performance.

This suggests that any initial observed effects are likely driven by unobserved firm- or sector-level characteristics rather than the bunching behavior itself. The significance of these effects without controls may reflect omitted variable bias, which is mitigated by adding sector and regional fixed effects, highlighting the importance of these factors in accurately estimating the impact of bunching on performance. These findings imply that strategic size adjustments around the eligibility threshold do not have a lasting impact on firm performance.

A key factor is that the New Sabatini subsidy does not require firms to maintain eligibility continuously over time to benefit from the subsidy, indeed firms only need to meet eligibility thresholds initially to qualify. Apparently, this feature may encourage short-term adjustments in terms of size to qualify for the subsidy, but not significant in this study, without committing to permanent size management. This could explain why bunching behaviour shows no lasting positive or negative effect on *"EBITDA* or *"ADJROA"*, suggesting that firms are free to return to their pre-subsidy management practices after qualifying.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
			Sub = 1			
	(1)	(2)	(3)	(4)	(5)	(6)
Below	0.3930183	0.5478674	0.4559005	0.6188403	0.6193983	0.4685084
	(0.608635)	(0.5563707)	(0.5471598)	(0.6460065)	(0.6882542)	(0.6726546)
Observations	1,118	1,416	1,653	687	905	1,091
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 16: Logit Regression Results for Subsidy Allocation

This figure presents the results from a logit model examining how changes the likelihood of receiving the New Sabatini subsidy in 2017 or 2018 between those identified as bunching in 2015 or 2016, *below*, and the *naturally eligible*. The model includes control variables and fixed effects for sector and province to control for unobserved heterogeneity across industries and regions. Standard errors (in parenthesis) are clustered at the firm level. Multiple bandwidths are used (18%, 20%, and 22%) to capture firms near the 43-million total assets threshold (Columns 1-3) and the 50-million sales threshold (Columns 4-6), focusing on firms on the left side of each threshold. The *below* variable is not statistically significant across any of the bandwidths, indicating no significant association between eligibility manipulation and the probability of obtaining this specific subsidy.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
			Ln(Grant amount + 1)			
	(1)	(2)	(3)	(4)	(5)	(6)
Below	0.1050525	0.1498502	0.110541	0.0144817	0.1044461	0.0873547
	(0.2564108)	(0.2443964)	(0.2379815)	(0.3262599)	(0.3328419)	(0.3170626)
R - squared	0.1748	0.1623	0.1582	0.1579	0.1580	0.1545
Observations	2,297	2,628	2,963	1,810	2,071	2,336
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 17: OLS Regression Results for Grant Amounts

This figure presents the results estimated using pooled Ordinary Least Squares (OLS) regressions. The dependent variable is the natural logarithm of the grant amount plus 1 obtained in 2017 or 2018. *below* distinguishes the *opportunistic eligible* in 2015 and 2016 from the *naturally eligible* firms. The regressions include controls for firm characteristics, as well as fixed effects for year, industry, and region to account for unobserved heterogeneity. Multiple bandwidths are used (18%, 20%, and 22%) to capture firms near the 43-million total assets threshold (Columns 1-3) and the 50-million sales threshold (Columns 4-6), focusing on firms on the left side of each threshold. Standard errors (in parenthesis) are clustered at the firm level to address repeated observations over time. The results indicate that there is no statistically significant evidence that firms classified as *opportunistic eligible* received larger grant amounts compared to *naturally eligible* firms.

	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	EBITDA among beneficiaries (sub = 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
did_a	-0.1024291***	0.0452663	0.0195665			
	(0.0155853)	(0.0340521)	(0.0201327)			
did_s				0.0123317	0.0020086	-0.0122347
				(0.0196271)	(0.0075307)	(0.0080202)
R - squared	0.0042	0.3737	0.9869	0.0012	0.9083	0.9701
Observations	544	544	528	338	338	323
Controls	NO	YES	YES	NO	YES	YES
nace_2_digit sector X year FE	NO	NO	YES	NO	NO	YES
province X year FE	NO	NO	YES	NO	NO	YES

Table 18: Difference-in-Differences Results: Impact of Bunching on EBITDA

This figure presents the results from a Difference-in-Differences (DID) model with EBITDA as the dependent variable. Specifically, *did_a* and *did_s* are the interaction terms that equal 1 if the firm is identified as a ”buncher” in 2015 or 2016 and if the period is after 2017, aiming to capture the long-term effects of bunching behavior. The analysis is limited to subsidy beneficiaries to isolate the effects of bunching, controlling for any direct impact from the subsidy. Control variables are sequentially added, followed by fixed effects to account for unobserved heterogeneity across industries, and regions. Standard errors (in parentheses) are clustered at the firm level.

	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	ADJROA among beneficiaries (sub = 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
did_a	-0.0618581 ***	-0.0356454***	0.0061086			
	(0.0135608)	(0.0147161)	(0.0266856)			
did_s				0.0009725	0.0240127	-0.0153903
				(0.0248571)	(0.0205475)	(0.024852)
R - squared	0.0250	0.2993	0.8299	0.0002	0.4400	0.8087
Observations	544	544	528	338	338	323
Controls	NO	YES	YES	NO	YES	YES
nace_2_digit sector X year FE	NO	NO	YES	NO	NO	YES
province X year FE	NO	NO	YES	NO	NO	YES

Table 19: Difference-in-Differences Results: Impact of Bunching on ADJROA

This figure presents the results from a Difference-in-Differences (DID) model with ADJROA as the dependent variable. Specifically, *did_a* and *did_s* are interaction terms that equal 1 if the firm is identified as a "buncher" in 2015 or 2016 and if the period is from 2017 onward, aiming to capture the long-term effects of bunching behavior. The analysis is limited to subsidy beneficiaries to isolate the effects of bunching, controlling for any direct impact from the subsidy. Control variables are sequentially added, followed by fixed effects to account for unobserved heterogeneity across industries and regions. Standard errors (in parentheses) are clustered at the firm level.

7 Robustness checks and Alternative specifications

This section presents a series of robustness checks and alternative specifications.

1. Identifying key thresholds: the aim is to distinguish between firms that adjusted their assets and those that adjusted their sales in 2015 or 2016, verifying whether the results are consistent around each specific threshold. Specifically, two new binary variables are created: *below_a*, which equals 1 if the firm managed its total assets strategically in 2015 or 2016 and *below_s*, which captures the strategic sales management in the same years. These definitions follow the explanation of below, such as if the firm decreased either its total assets or sales in 2015, it remains in the bunching category in 2016.

The logit model and OLS regressions are then fitted within the left bins around 43-million-total assets and 50-million-total sales thresholds, specifically 18%, 20% and 22% intervals. The object is to verify if Firms that may be allegedly defined as an *"opportunistic eligible"* increases the likelihood of receiving the subsidy or affects the grant amount in comparison to *"naturally eligible* firms, that is why only the region below the threshold is considered.

Similarly to the baseline model incorporating *below*, the coefficients for *below_s* and *below_a* are not statistically significant at any of the considered intervals neither regarding the likelihood nor the grant amount received (Table 21 and Table 22). This suggests that adjustments in total assets or sales in 2015 or 2016, examined specifically, do not have a relationship with the changes in the New Sabatini program. These results reinforce the interpretation that firms may not gain substantial benefits from manipulating financial metrics to meet the New Sabatini's criteria.

2. Definition of industries: The models of equations 2 and 3 are then run changing the fixed effects from a two-digit Nace code to a three-digit Nace code, in this way, the sectors are broken down into sub-industries. Thereby, if firms behave differently depending on the sub-industry they belong to, three-digit nace codes can handle the distinctions better. With a more detailed industrial classification, the sector fixed effect should help to account for potential unobserved factors, such as competition levels or industry-specific costs. (See

Di Marzio et al. (2024)

The results in Table 23 and in Table 24 are consistent with the baseline models, showing that opportunistic behaviour does not affect significantly either the likelihood of receiving the subsidy, or the amount obtained. This robustness across different levels of industry classification supports the conclusion that the New Sabatini does not create an incentive for opportunistic financial adjustments.

3. Alternative comparison - *opportunistic eligible* vs *non-eligible*: The baseline model defined in equation 3 is used again with the same specifications but now comparing *opportunistic eligible*, those that strategically position themselves below the threshold, and *not eligible*, those that consistently remain above both the total assets and sales thresholds. The equations 2 and 3 are re-performed within the 18%, 20% and 22% bins around the 43-million-total assets and 50-million-total sales thresholds.

This setup allows us to assess whether jumping below the thresholds may be significantly beneficial for *opportunistic eligible*, compared to the counterfactual that decide to maintain their size above the thresholds. Indeed, it is then crucial to consider that there is an application process, meaning that not all the firms that engage in bunching behaviour necessarily apply for the subsidy. Now this aspect is captured, making it relevant to evaluate whether *opportunistic eligible* significantly obtain greater amounts compared to those that maintain their size above the thresholds in both 2015 and 2016. If the results show a significant advantage for the opportunistic group, this suggests that firms might indeed adjust strategically their size to apply for the subsidy. On the contrary, if there is not a significant difference in grant amounts, this would indicate that the policy may not provide strong enough incentives leading to adjustments among firms.

According to the results of Table 25, having *below* equal to 1 does not significantly affect the grant amount received compared to those that did not sacrifice growth. This finding implies that, although some firms do change, these adjustments are not strongly associated with an purpose to qualify for the New Sabatini. Therefore, the benefit of the subsidy may not exert enough influence to encourage strategic behavior.

4. Alternative specification of *bunching*: To explore potential bunching behaviour, a straightforward visual method was employed through the representation of histograms with small bins to depict the distributions of sales and assets for the years 2014, 2015, and 2016. An essential step is the procedure to identify an appropriate bunching window to accurately define the bunching mass. The window should neither be too narrow, as this may result in the exclusion of relevant firms – false negative -, nor too broad, it may incorrectly classify firms as bunchers – false positive, as explained by Bosch et al. (2020) and Dekker and Schweikert (2021). To mitigate such biases, the data-driven method used relies on comparing the distribution in the pre-announcement period (the year 2014) with the the year of the announcement (2015) and the post announcement (2016). This approach accounts for both firms that adapt immediately and those that adjust in the subsequent year, thereby incorporating potential optimization frictions that influence the decision-making process by delaying firms' responses. (See Kleven and Waseem (2013) and Chetty (2012)).

Two binary variables were created, firstly, *bunching_sales_distrib*, which equals 1 if a firm falls within the 5% sales bins immediately below the sales cutoff point in either 2015 or 2016, as firms may apply using the financial statements from either year. (See Table 20). This classification identifies 493 firms as *bunchers* in terms of sales.

The second variable is *bunching_assets_distrib*, which equals 1 if the observation falls within the 2.32% bins below the assets threshold in 2016, as from the non-parametric there is evidence of a jump only in that year. In this case, 142 are identified as bunchers based on assets adjustments (see Table 20).

Among those classified as bunchers, 10 firms recognized as asset jumpers obtained the New Sabatini, while a total of 15 beneficiaries adjusted their sales.

Conversely, firms that fall outside the specified ranges but within the 20% bins below the threshold are categorized as *naturally eligible*, meaning they qualify for the subsidy without engaging in any manipulation. (See Saez (2010)).

	sub		
	0	1	Total
bunching sales = 0	21,068	1,433	22,501
bunching sales = 1	478	15	493
bunching assets = 0	21,404	1,438	22,842
bunching assets = 1	142	10	152
Total (for sub)	21,546	1,448	22,994

Table 20: Distribution of Firms by Bunching Behaviour in Sales and Assets with Subsidy Beneficiaries

This figure illustrates the distribution of firms in 2015 and 2016 classified by their proximity to the sales and assets thresholds, identifying those that engage in bunching behavior. The binary variable *bunching_sales* marks firms within 5% bins below the sales cutoff in either 2015 or 2016. Similarly, *bunching_assets* denotes firms within 2.32% bins below the assets threshold in 2016. The variable *sub* indicates subsidy beneficiaries within this distribution.

The baseline equations 3 and 2 are adapted to reflect the new bunching specifications, specifically adjusting the variables of interest and the chosen intervals. This time the comparison is between bunching and non-bunching.

Probit: First, a probit model is estimated with the New Sabatini subsidy (*"sub"* as the binary dependent variable, coded as 1 if the firm obtained it. The choice of the probit model, which assumes a normal error distribution, was made due to convergence issues encountered with the logit model. Indeed, logit models are particularly sensitive to limited variability within predictor combinations. Although the logit model is commonly used for binary outcomes, the probit model provides stable estimates without convergence issues. Additionally, the interpretation of coefficients remains consistent, as both models estimate the probability of an outcome.

The model is specified as:

$$\text{sub}_{f,t+1} = \beta \cdot \text{bunching}_{f,t} + \delta \cdot \text{controls}_{f,t} + \gamma \cdot \text{sector}_{f,t} + \theta \cdot \text{province}_{f,t} + \epsilon_{f,t} \tag{5}$$

Control variables, such as firm_age", "ROA", "cash holdings", "leverage", "ROE", the logarithm of sales and assets, "liquidity" and "capital", are lagged to align with the same years as the bunching variables. Precisely, the effect of asset bunching was evaluated only in 2016, where significant evidence of bunching was observed.

The model also includes sector - year and province - year fixed effects and is run within the 18%, 20% and 22% bins around the 43-million-total assets and 50-million-sales thresholds, comparing thus bunching and non-bunching. The errors are then clustered at the firm level.

The coefficient of interest, denoted as β, quantifies the difference in the probability of obtaining the New Sabatini subsidy between firms that do not engage in bunching and those that manipulate their distributions. Specifically, it measures this difference, first, with respect to firms that manipulate their assets distribution *(bunching_assets_distrib=1)*. In addition, the effect of asset bunching was evaluated only in 2016, where significant evidence of bunching was observed. Then with respect to those that manipulate their sales distribution *(bunching_sales_distrib=1)*.

OLS regressions: The second step involves assessing the effect of bunching on the grant amount received. The rationale behind is that if a firm sacrifices growth to qualify, it implies that the subsidy is perceived as valuable. Intuitively, the expectation is that being opportunistically positioned just below the cutoff point would result in a higher grant amount compared to naturally eligible firms.

To investigate this aspect, an ordinary least square (OLS) regression is modeled:

$$Y_{t+1} = \beta \cdot \mathit{bunching}_{f,t} + \delta \cdot \text{controls}_{f,t} + \gamma \cdot \text{sector}_{f,t} + \theta \cdot \text{province}_{f,t} + \epsilon_{f,t} \tag{6}$$

Here, the dependent variable Y_(t+1) is the natural logarithm of the grant amount plus 1. The rest of the model structure is unchanged from equation 3, both regarding the control variables and fixed-effects. Standard errors are clustered at the company level. The regressions are run within the 18%, 20% and 22% bandwidth around the 50-million sales and 43-million assets thresholds. Similarly to above, the effect of asset bunching is evaluated only in 2016.

Again, the coefficient of interest is β, that estimates the difference in grant amounts between bunching and non-bunching. It first evaluates this difference based on whether firms manipulate their assets distribution *(bunching_assets_distrib)*, then considers manipulation in sales distribution *(bunching_sales_distrib)*. This provides evidence on whether bunching behavior results in greater benefits in terms of grant amounts.

Main results: From columns (1) to (3) of Table 26 there are the estimated coefficient from a probit model comparing bunching and non-bunching firms within the specified interval around the 43-million-assets threshold. Then from columns (4) to (6) the estimates refer to the 50-million sales threshold. In both cases, the estimated coefficients for bunching, with the subsidy dummy *("sub")* as the dependent variable, are not statistically significant at the 10% level. In other words, firms that managed to lower their sales or total assets in 2015 or 2016 did not exhibit a higher probability of obtaining the New Sabatini subsidy in 2017 or 2018.

A similar conclusion is drawn from the OLS regression when changing only the dependent variable to the natural logarithm of the grant amount plus 1, as shown in Table 27. Bunching firms are not more likely to receive the grant, but also they do not secure higher grant amounts compared to those that did not change. This could be given by the fact that, as already noted, the primary beneficiaries of the subsidy are indeed firms located well outside the selected bandwidth and not belonging to the bunching definition. Thus, although the bunching phenomenon is observable, the New Sabatini program cannot be considered as the driving force behind it.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
				Sub = 1		
	(1)	(2)	(3)	(4)	(5)	(6)
below_a	0.4987268	0.5478674	0.5286305			
	(0.6222667)	(0.5563707)	(0.558138)			
below_s				0.7154213	0.6626126	0.5061572
				(0.6544585)	(0.7002856)	(0.6842936)
Observations	1,118	1,416	1,653	687	905	1,091
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 21: Logit Regression Results on the Likelihood of Subsidy Eligibility

This figure presents the results from a logit regression analyzing whether firms that adjusted their assets or sales in 2015 and 2016 to stay below critical thresholds (43 million for total assets and 50 million for total sales) had a greater likelihood of receiving the subsidy in 2017 and/or 2018. The regression is computed only within bins on the left side of each threshold. Two binary indicators, *below_a* and *below_s*, represent firms that strategically managed their assets and sales, respectively, within 18%, 20%, and 22% intervals below these thresholds. The analysis includes control variables and fixed effects to account for industry-specific and regional factors. Standard errors (in parenthesis) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	Ln(Grant amount + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
below_a	0.1229215	0.1707573	0.1259791			
	(0.2659197)	(0.2542234)	(0.2470317)			
below_s				0.0300379	0.1153674	0.1090488
				(0.3384542)	(0.3480602)	(0.3301803)
R - squared	0.1748	0.1623	0.1582	0.1579	0.1580	0.1546
Observations	2,297	2,628	2,963	1,810	2,071	2,336
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 22: OLS Regression Results on the Grant Amount

This figure presents the results from an OLS regression where the dependent variable is the logarithm of the grant amount plus 1, analyzing whether firms that adjusted their assets or sales in 2015 and 2016 to stay below critical thresholds (43 million for total assets and 50 million for total sales) received a greater grant amount in 2017 and/or 2018. The regression is computed only within bins on the left side of each threshold. Two binary indicators, *below_a* and *below_s*, represent firms that strategically managed their assets and sales, respectively, within 18%, 20%, and 22% intervals below these thresholds. The analysis includes control variables and fixed effects to account for industry-specific and regional factors. Standard errors (in parenthesis) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
			Sub = 1			
	(1)	(2)	(3)	(4)	(5)	(6)
Below	0.9461848	0.95699	0.8851222	0.1465948	-0.25281	-0.2092282
	(0.7832205)	(0.7416216)	(0.6816214)	(0.8195176)	(0.7696176)	(0.7232684)
Observations	734	983	1,202	381	587	733
Controls	YES	YES	YES	YES	YES	YES
nace_3_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 23: Logit Regression Results on the Likelihood of Subsidy Eligibility (Three-Digit NACE Code)

This figure presents the results from a logit regression analyzing whether firms that adjusted their assets or sales in 2015 and 2016 to stay below critical thresholds (43 million for total assets and 50 million for total sales) had a greater likelihood of receiving the subsidy in 2017 and/or 2018. The regression is computed only within bins on the left side of each threshold. Two binary indicators, *below_a* and *below_s*, represent firms that strategically managed their assets and sales, respectively, within 18%, 20%, and 22% intervals below these thresholds. The analysis includes control variables and three-digit NACE code fixed effects to capture industry-specific and regional variations at a sub-industry level. Standard errors (in parenthesis) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	Ln(Grant amount + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Below	0.1259762	0.1602773	0.0859544	0.0382351	0.1127691	0.0391543
	(0.2977527)	(0.2785494)	(0.2695501)	(0.3369892)	(0.3444105)	(0.3302303)
R - squared	0.2620	0.2444	0.2323	0.2827	0.2756	0.2665
Observations	2,297	2,628	2,963	1,810	2,071	2,336
Controls	YES	YES	YES	YES	YES	YES
nace_3_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 24: OLS Regression Results on Grant Amount (Three-Digit NACE Code)

This figure presents the results from an OLS regression where the dependent variable is the logarithm of the grant amount plus 1, analysing whether firms that adjusted their assets or sales in 2015 and 2016 to stay below critical thresholds (43 million for total assets and 50 million for total sales) received a greater grant amount in 2017 and/or 2018. The regression is computed only within bins on the left side of each threshold. Two binary indicators, *below_a* and *below_s*, represent firms that strategically managed their assets and sales, respectively, within 18%, 20%, and 22% intervals below these thresholds. The analysis includes control variables and three-digit NACE code fixed effects to capture sub-industry-specific and regional variations. Standard errors (in parenthesis) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	Ln(Grant amount + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Below	0.6580666	0.5905193	0.5198963	0.1662331	0.2285	0.2259749
	(0.5221632)	(0.4392978)	(0.4234951)	(0.2269427)	(0.2125662)	(0.2111645)
R - squared	0.4757	0.4687	0.4186	0.3334	0.2730	0.2671
Observations	563	616	666	621	691	743
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 25: OLS Regression Results Comparing Opportunistic Eligible vs. Non-Eligible Firms

This figure presents the results from an OLS regression where the dependent variable is the logarithm of the grant amount plus 1, analyzing whether firms classified as *opportunistic eligible* versus *non-eligible*, based on their financial adjustments in 2015 and 2016 to remain below critical thresholds (43 million for total assets and 50 million for total sales), received a greater grant amount in 2017 and/or 2018. A binary variable (*below*) represents firms that strategically managed their assets and sales, respectively, within 18%, 20%, and 22% intervals below these thresholds. The analysis includes control variables and two-digit NACE code fixed effects to account for industry-specific and regional variations, ensuring a robust assessment of differences in grant amounts between *opportunistic eligible* and *non-eligible firms.* Standard errors (in parenthesis) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	Sub = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
bunching_assets_distrib	0.1489109	0.1703514	0.1929951			
	(0.1947147)	(0.1913324)	(0.1894449)			
bunching_sales_distrib				-0.147146	-0.1829796	-0.195521
				(0.1522157)	(0.1513377)	(0.1435094)
Observations	1,112	1,322	1,553	1,509	1,829	3,971
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 26: Logit Regression Results Comparing *Bunching* vs. *Non-Bunching* Firms.

This figure presents the results from a logit regression analyzing the likelihood of receiving a grant for firms classified as *bunching* versus *non-bunching* based on their financial adjustments in 2015 and 2016 to stay just below critical thresholds (43 million for total assets and 50 million for total sales). The variable *bunching_assets_distrib* identifies firms just below the assets threshold in 2016, while *bunching_sales_distrib* identifies firms just below the sales threshold in 2015 and 2016. The analysis includes control variables and two-digit NACE code fixed effects to account for industry-specific and regional variations within the 18%, 20%, and 22% intervals just below these thresholds. Standard errors (in parentheses) are clustered at the firm level.

	bw 18	bw 20	bw 22	bw 18	bw 20	bw 22
	Around the 43 million total assets threshold			Around the 50 million sales threshold		
	Ln(Grant amount + 1)					
	(1)	(2)	(3)	(4)	(5)	(6)
bunching_assets_distrib	0.1715601	0.1674407	0.1711937			
	(0.2142488)	(0.215791)	(0.216853)			
bunching_sales_distrib				-0.083588	–0.1318025	-0.122306
				(0.1054139)	(0.107425)	(0.1042286)
R - squared	0.1281	0.1254	0.1255	0.1063	0.1075	0.1076
Observations	1,965	2,210	2,445	3,089	3,467	3,826
Controls	YES	YES	YES	YES	YES	YES
nace_2_digit sector X year FE	YES	YES	YES	YES	YES	YES
province X year FE	YES	YES	YES	YES	YES	YES

Table 27: OLS Regression Results Comparing *Bunching* vs. *Non-Bunching Firms*

This figure presents the results from an OLS regression analyzing the grant amount awarded to firms classified as *bunching* versus *non-bunching* based on their financial adjustments in 2015 and 2016 to stay just below critical thresholds (43 million for total assets and 50 million for total sales). With *bunching_assets_distrib* defining firms just below the assets threshold in 2016, and *bunching_sales_distrib* defining firms just below the sales threshold in 2015 and 2016. The analysis includes control variables and two-digit NACE code fixed effects to account for industry-specific and regional variations within the 18%, 20%, and 22% intervals just below these thresholds. Standard errors (in parenthesis) are clustered at the firm level.

8 Policy Implications and Future Directions

The findings of this study provide insights into subsidy programs designed similarly to the New Sabatini. The evidence suggests that opportunistic size management, employed to qualify, does not lead to a higher probability of receiving subsidies or larger amounts. Therefore, firms that engaged in bunching by adjusting their total assets or sales did not significantly benefit more from the subsidy program than those naturally eligible, such as already categorized as small or medium-sized enterprises.

In addition, although some evidence of bunching is observed, the lack of long-term effects on firm performance indicates that temporary adjustments in size to meet eligibility requirements have limited impact. Probably the design of the New Sabatini program, which requires firms to meet eligibility thresholds only at the time of application, may explain these findings. This structure allows firms to make short-term adjustments, even though not significant in this study, to qualify for the subsidy without needing to maintain these adjustments over time. Thereby firms avoid any substantial impact on long-term performance. Furthermore, the primary beneficiaries of the subsidy are small firms that are naturally eligible, suggesting that bunching may be less prevalent under the New Sabatini program compared to other subsidy schemes. (See Acharya et al. (2022), Di Marzio et al. (2024) and Zanoni et al. (2024)). These results may be driven by the fact that the New Sabatini does not create strong incentives for long-term size management or growth-oriented adjustments, as firms are not required to maintain their eligibility status after the initial application. However, other more economically relevant subsidies may encourage firms to adjust their size, operations, or financial reporting practices, with the aim of maintaining compliance over time or maximizing benefits.

On the other hand, several limitations should be considered when interpreting these results. First, even though the analysis is conducted within intervals, the lack of firm fixed effects may introduce omitted variable bias that may influence both the financial manipulation decision and subsidy outcome. Indeed, those could control for unobserved and time-invariant characteristics specific to each firm, for instance, managerial quality, and long-term strategy. However, the current models aim indeed to reach a balance between the observable firm characteristics and maintaining sufficient variability across firms. As the limited within-firm variability over time when including firm fixed effects would lead to a drop in a significant number of firms.

Additionally, the selection of the bunching window used in the robustness check for another definition of bunching may not capture all the bunching responses. Non-parametric evidence follows the approach in the bunching literature, such as the creation of histograms with bins. (See Saez (2010)). Despite this, some firms could fall outside the selected bandwidths. While this limitation could introduce some bias, multiple models have been run to mitigate its impact. By employing several specifications and robustness checks, the analysis aims to ensure that the observed results are not driven by the specific choice of bandwidth. These additional models reinforce the conclusion that any potential bias, related to the selection of the bandwidth, does not significantly alter the relationship between bunching behavior, the New Sabatini subsidy and the firms' performance in the long-run.

Lastly, the New Sabatini program may have unique characteristics, such that it is not possible to infer of findings to other subsidy or incentive programs. Future research could explore again these thresholds, uniquely used for subsidies, to determine whether similar behavioral patterns and outcomes are observed under other subsidy structures in Italy. This would help to validate the findings or uncover the driving forces behind the spikes observed in the non-parametric analysis.

Based on the above findings, another possible direction for future research could be to explore the impact of continuous compliance of the eligibility requirements. Under such a policy design, firms that bunch would need to maintain eligibility throughout the subsidy period. This approach raises open questions: on one hand, continuous eligibility requirements could discourage short-term bunching behavior, leading to more sustainable adjustments. On the other hand, it could create incentives for firms to remain small, potentially destroying growth.

Further works could then apply a dynamic perspective, by examining whether bunching firms go back to their pre-subsidy size or financial behavior once they receive the subsidy. Understanding the sustainability of these financial adjustments would provide a clearer picture of the true long-term effects of subsidy programs on firm growth and competitiveness.

9 Conclusion

By exploiting the New Sabatini program, this research provides an understanding of the effect of threshold-dependent policies on firms' behaviour, focusing on strategic financial adjustments and size management.

By examining firm responses to a policy change announcement in 2015 and 2016 around the €43 million total assets and €50 million sales thresholds, this study assesses whether financial eligibility criteria influence companies' decisions to adjust their size to qualify for government support. Contrary to expectations, the findings suggest that the New Sabatini subsidy program did not significantly drive bunching behavior, indicating that the incentive may not have been sufficiently compelling to motivate firms to alter strategically their size. This result aligns with prior research by Klimsa and Ullmann (2022) and Gelber et al. (2014), who showed that not all size-based regulatory incentives translate into significant behavioral responses.

Specifically, firms identified as engaging in bunching in 2015 or 2016 did not exhibit a higher likelihood of securing the New Sabatini grant nor receive larger grant amounts in 2017 or 2018 compared to their naturally eligible counterparts who were already below either the €43 million total assets or €50 million sales thresholds.

In addition, after incorporating control variables and fixed effects, the difference-in-differences (DiD) model, which examines the long-term impact of bunching on firm performance, did not yield significant results. That means that bunching behavior did not translate into meaningful differences in key performance metrics, such as EBITDA or adjusted return on assets (ROA), in the long term.

To ensure the robustness of the results, several bandwidths and model specifications are employed. However, the conclusions are consistent over different model setups, the effects of bunching lack of significance.

These results provide a comprehensive view of the limited behavioral responses associated with the New Sabatini subsidy, suggesting that the program was not a significant driver of strategic financial adjustments observed in 2015 and 2016. This aligns with the fact that the primary beneficiaries of the New Sabatini program in 2017 and 2018 were small firms, that means already eligible without needing to adjust.

The findings also underscore the design implications of size-dependent subsidies. Indeed, the New Sabatini program requires to meet either one of the two eligibility thresholds only at the time of application, rather than on a continuous basis, thus, potentially reducing long-term distortions in firm growth. This flexibility allows firms to grow after the application, thereby avoiding the pitfalls of permanent size constraints, which can restrict growth and innovation. These insights emphasize the importance of designing subsidy policies that minimize adverse incentives while promoting sustainable firm development.

Referring to policymakers, the study highlights the need to carefully consider the structure and duration of eligibility requirements to ensure that economic goals are met without generating unintended market distortions.

Further investigation could also examine more the patterns around the subsidy-specific thresholds used in this thesis, which are uniquely applied for subsidies qualification in Italy.

Additionally, further research could explore how short-term adjustments, made by the firm to apply, influence the performance in the long run. Indeed, firms may tend to return to their pre-application status. This study will provide insights into how policy regulations shape firms growth, resources allocation, and market dynamics.

Moreover, another area of interest could involve evaluating the effects of demanding continuous compliance with the requirements. From one hand, this setup could disincentive short-term adjustments, while encouraging firms to find strategies more oriented to the the long-run. On the other, such a design might also incentivize firms to remain small over time, thus penalizing their development. Understanding the balance between encouraging firm to apply and promoting long-term growth is essential to design effective economic policies.

References

Acharya, V. V., Crosignani, M., Eisert, T., and Steffen, S. (2022). Zombie Lending: theoretical, international, and historical perspectives. *Annual Review of Financial Economics*, 14(1):21–38.

Almunia, M. and Lopez-Rodriguez, D. (2018). Under the radar: The effects of monitoring firms on tax compliance. *American Economic Journal Economic Policy*, 10(1):1–38.

Bernard, D., Burgstahler, D., and Kaya, D. (2018). Size management by European private firms to minimize proprietary costs of disclosure. *Journal of Accounting and Economics*, 66(1):94–122.

Bosch, N., Dekker, V., and Strohmaier, K. (2020). A data-driven procedure to determine the bunching window: an application to the Netherlands. *International Tax and Public Finance*, 27(4):951–979.

Chetty, R. (2012). Bounds on Elasticities with Optimization Frictions: A synthesis of micro and macro evidence on labor supply. *Econometrica*, 80(3):969–1018.

Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *The Quarterly Journal of Economics*, 126(2):749–804.

Crouzet, N. and Mehrotra, N. R. (2020). Small and Large Firms over the Business Cycle. *American Economic Review*, 110(11):3549–3601.

Dekker, V. and Schweikert, K. (2021). A comparison of different data-driven procedures to determine the bunching window. *Public Finance Review*, 49(2):262–293.

Di Marzio, I., Mocetti, S., and Rubolino, E. (2024). Market Externalities of Tax Evasion. *Social Science Research Network - SSRN*.

Dichev, I. D., Graham, J. R., Harvey, C. R., and Rajgopal, S. (2013). Earnings quality: Evidence from the field. *Journal of Accounting and Economics*, 56(2-3):1–33.

European Commission (2003). Recommendation no. 2003/361/ec of may 6, 2003 concerning the definition of micro, small and medium-sized enterprises.

Gelber, A. M., Jones, D., and Sacks, D. W. (2014). Earnings Adjustment Frictions: Evidence from the Social Security Earnings Test. *SSRN Electronic Journal*.

Gourio, F. and Roys, N. (2014). Size-dependent regulations, firm size distribution, and reallocation. *Quantitative Economics*, 5(2):377–416.

Gunny, K. A. (2010). The Relation Between Earnings Management Using Real Activities Manipulation and Future Performance: Evidence from Meeting Earnings Benchmarks*. *Contemporary Accounting Research*, 27(3):855–888.

Harju, J., Matikka, T., and Rauhanen, T. (2016). The Effects of Size-Based Regulation on Small Firms: Evidence from Vat Threshold. *SSRN Electronic Journal*.

Huang, Y. (2022). Government subsidies and corporate disclosure. *Journal of Accounting and Economics*, 74(1):101480.

Khandker, S., Koolwal, G. B., and Samad, H. (2009). *Handbook on Impact Evaluation*. The International Bank for Reconstruction and Development / The World Bank.

Kleven, H. J. (2016). Bunching. *Annual Review of Economics*, 8(1):435–464.

Kleven, H. J. and Waseem, M. (2013). Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan *. *The Quarterly Journal of Economics*, 128(2):669–723.

Klimsa, D. and Ullmann, R. (2022). Threshold-dependent tax enforcement and the size distribution of firms: evidence from Germany. *International Tax and Public Finance*, 30(4):1002–1035.

Ministry of Enterprises and Made in Italy (2017). Nuova sabatini statistics report. Accessed: 2024-10-31.

Ministry of Enterprises and Made in Italy (2018). Nuova sabatini statistics report. Accessed: 2024-10-31.

Moreta, A. (2024). Reporting regulation and private firms' bank credit. *SSRN Electronic Journal*.

OECD (2014). Oecd studies on smes and entrepreneurship: Italy. Technical report, OECD Publishing, Paris. © OECD 2014.

Pappas, K., Walker, M., Xu, A. L., and Zeng, C. (2024). Government subsidies and income smoothing. *Contemporary Accounting Research*.

Penman, S. H. (2013). *Financial Statement Analysis and Security Valuation*. McGraw-Hill Education.

Registro Nazionale degli Aiuti di Stato (2024). Registro nazionale degli aiuti di stato. Accessed: 2024-11-04.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3):335–370.

Saez, E. (2010). Do taxpayers bunch at kink points? *American Economic Journal Economic Policy*, 2(3):180–212.

Schwartz, G. and Clements, B. (1999). Government subsidies. *Journal of economic surveys*, 13(2):119–148.

Studenmund, A. (2014). *Using Econometrics: A practical guide*. Pearson, sixth edition.

Wooldridge, J. M. (2001). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Xu, R., Shen, Y., Liu, M., Li, L., Xia, X., and Luo, K. (2022). Can government subsidies improve innovation performance? Evidence from Chinese listed companies. *Economic Modelling*, 120:106151.

Zanoni, W., Carrillo-Maldonado, P., Pantano, J., and Chuquimarca, N. (2024). Irrational bunching? tax regimes, brackets, and taxpayer behaviors. Technical report, Inter-American Development Bank, Country Department Andean Group.

Appendix

A Additional Figures

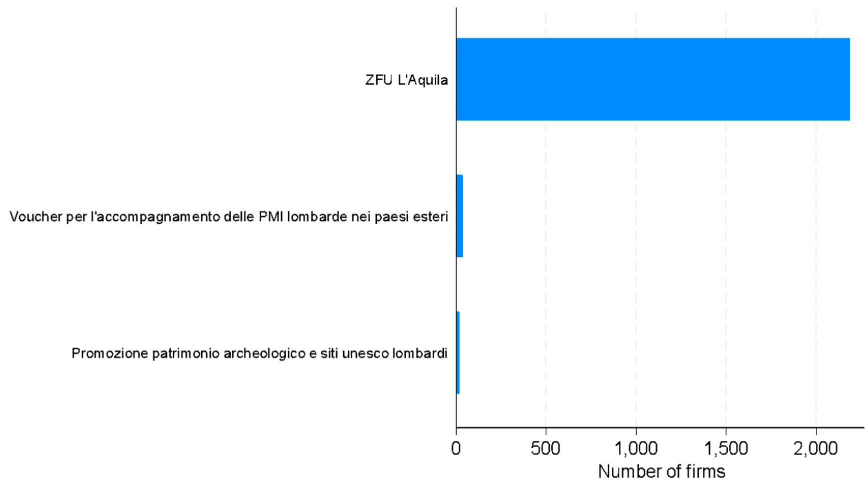

Figure 12: Beneficiaries in 2013

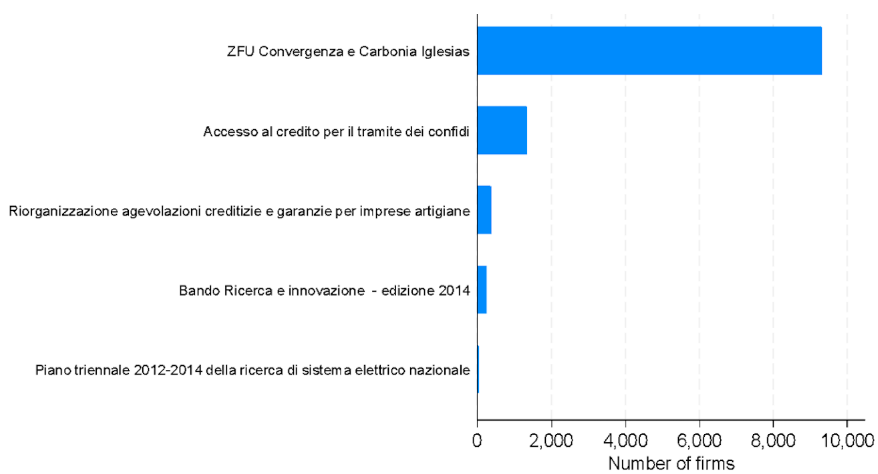

Figure 13: Beneficiaries in 2014

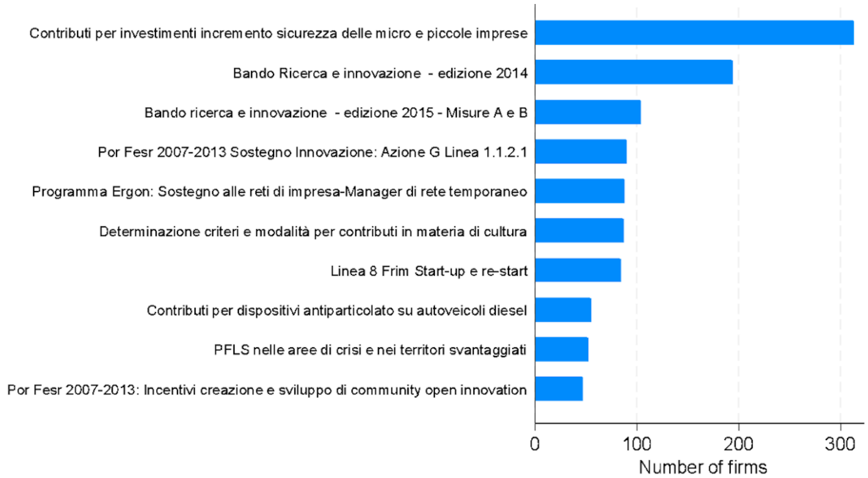

Figure 14: Beneficiaries in 2015

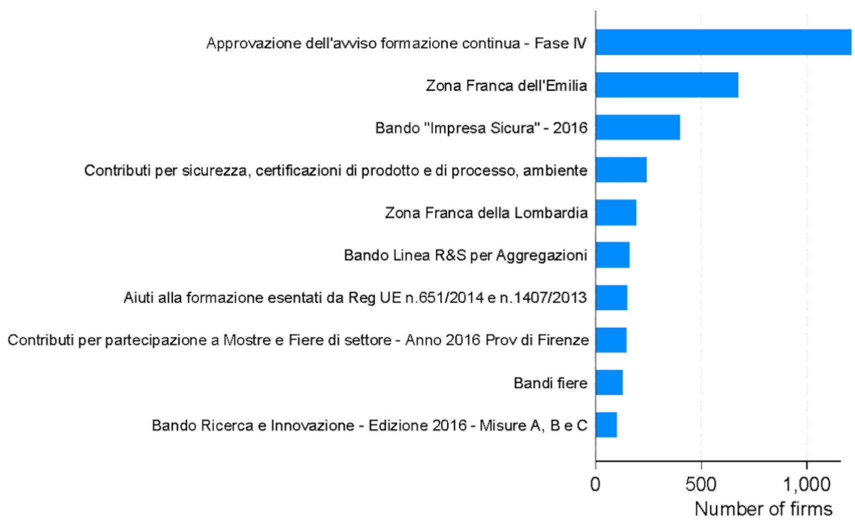

Figure 15: Beneficiaries in 2016