Essays in Public Economics

Inauguraldissertation

zur Erlangung des akademischen Grades eines Doktors
der Wirtschaftswissenschaften
der Universität Mannheim

vorgelegt von

Tania Guerra Rosero

Herbst-/Wintersemester 2025

Abteilungssprecher:	Prof. Dr. Thomas Tröger
Vorsitzende der Disputation:	Prof. Dr. Antonio Ciccone
Referent:	Prof. Arthur Seibold, Ph.D.
Koreferent:	Prof. Dr. Eckhard Janeba
Tag der Disputation:	24 October 2025

Acknowledgements

I am grateful to the many people whose support made this journey possible. First of all, I would like to express my gratitude to Arthur Seibold for his guidance and continuous support throughout my Ph.D. studies. He taught me how to think about research, encouraged me to explore alternative ways to answer questions, and motivated me during the most challenging days. I am deeply grateful for the opportunity to learn from his experience. I would like to express my sincere gratitude to Eckhard Janeba for his support, especially during the final stage of my Ph.D. I appreciate his feedback, which sharpened my research ideas, as well as his encouragement to strengthen my projects. I thank Sebastian Siegloch for his feedback and supervision, from which I have greatly benefited. I appreciate the friendly and supportive environment he creates for his doctoral students. I am also grateful for the opportunity to discuss my research ideas with Antonio Ciccone and to receive his feedback.

I have always aspired to work on projects about my home country, Ecuador. This work was made possible by the support of the *Servicio de Rentas Internas* (SRI) in Ecuador. I thank the team at the *Departamento de Planificación Institucional* for their assistance with data access. I am also grateful to Cristian Chicaiza for sharing his expertise on the tax administration and the data, and to María Leonor Oviedo for her help coordinating my research visits.

I sincerely thank the administrative staff at the University of Mannheim for their guidance, which made my life in Germany much easier. I thank Julia Potapov, Marion Lehnert, Caroline Mohr, Golareh Khalilpour, and Kristina Kadel for their support.

I was lucky to share my Ph.D. journey with wonderful friends. Sabine, So Jin, Sandra, Felix, Chiara, Giacomo, Yiwei, and Thibault, thank you for the great times, whether studying or sharing dinners. I am also fortunate to have Andrés as a friend and co-author. I express my gratitude to my friends in Ecuador: Pris P., Caritol, Vero, Cassandra, Gina, Mayrita, Caro, Pris M., Juanita, Rommel, and Nico. Your constant support and belief in me, despite the distance and time zone differences, meant a lot to me.

Most importantly, I thank my family for their love, patience, and support. To my sister Vero and Fernando, your encouragement has carried me through. To my niece and nephew, Emi and Fernandito: thank you for always welcoming me back to Ecuador with excitement and love. Nothing brings me more joy than being your aunt. To my mother, my example of strength and courage in overcoming any circumstance: I am beyond grateful for all the sacrifices that you have made for me. To my late father: I wish you had seen this part of my life. Your memory is always in my heart.

Tania Guerra Rosero

Mannheim, September 2025

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Preface

This dissertation consists of three chapters that study questions in the field of public economics in the context of a developing country. Specifically, I investigate the effects of two tax enforcement policies on firm behavior in Ecuador and evaluate how governments can implement data-driven methodologies in tax monitoring programs. A unique characteristic of the policies studied in this dissertation is the government's reliance on private actors to improve tax collection. In Chapter 1, the government requires large firms to have their financial statements audited by third-party auditors. Chapters 2 and 3 focus on the Special Taxpayers Program in Ecuador, which has one component that requires large firms to collect taxes from their suppliers. Across chapters, I use rich tax administrative datasets, reduced-form methods, and machine learning algorithms.

Chapter 1 is titled *Third-Party Audits and Firm Behavior: Evidence from a Size-Base Enforcement Policy in Ecuador*, and is co-authored with Andrés Plúas López. In this chapter, we study the effects of a size-based enforcement policy in Ecuador that mandates third-party audits of tax returns for firms whose assets are above a threshold. Specifically, we exploit a policy reform implemented in 2016 that reduced the asset threshold that determines the firms that have to comply with the third-party audit obligation from USD 1 million to USD 500,000. The reduction of the threshold creates different monitoring levels and compliance costs around the threshold that are used to explore bunching responses and the effects of the audit obligation on the audited firms. Firms with assets below USD 500,000 are never required to have third-party audits. Firms with assets between USD 500,000 and USD 1 million are audited due to the change in the threshold. Firms with assets above USD 1 million are always required to have audited tax returns.

We first document a bunching response of firms that reduce their assets below the threshold to avoid the audit obligation. We observe more than four times as many firms at the threshold as we would expect in the absence of it. Firms use a cash flow strategy to bunch below the threshold: they reduce their current assets and current liabilities. Further, firms with a higher share of current assets are more likely to bunch. These findings have two policy implications that the government should consider when implementing an asset-based policy. First, reducing current assets to avoid the audit mandate may increase firms' exposure to future shocks. Second, the burden of the audit obligation falls on firms with a high composition of fixed assets.

We next turn to the effects of the audit mandate on the audited firms. We rely on a donut-hole RDD and exclude firms in the regions where firms strategically manipulate their assets to avoid the obligation. We use the bunching estimations to identify the *missing mass* and *bunching mass regions*. Firms that manipulate their assets come from the *missing mass region* and locate in the *bunching mass region*. After excluding these firms and comparing firms at each side of the threshold, we find that audited firms report 56% lower costs; however, we do not find an effect on reported tax liabilities. These findings suggest that third-party audits improve firms' reporting behavior, complementing the work of the tax administration, but they do not substitute its enforcement capabilities.

Chapter 2 is titled *Upstream Tax Enforcement Mechanisms: Evidence from VAT Withholding and Monitoring of Large Firms in Ecuador*. In this chapter, I study whether monitoring and assigning VAT withholding responsibilities to large taxpayers have effects on suppliers. Specifically, I investigate the effects of two enforcement policies. The first policy is the selection of large firms for the Special Taxpayers Program in 2018. Firms participating in this program are subject to intensified tax monitoring, and they are required to withhold VAT on transactions with suppliers (SRI, 2009). The program also aims to change the perceived risk of audits for the selected firms and their trade partners (Oliva and Aparicio, 2010). Suppliers are affected differently depending on their legal form. Corporate firms respond to the combined effect of VAT withholding and the government's monitoring of the large client, whereas individually owned firms are only exposed to the monitoring channel. This is because the latter are always subject to VAT withholding in transactions with large taxpayers, regardless of whether the client is a special taxpayer or not. The second policy is the extension of VAT withholding for transactions between special taxpayers in 2015.

To study the indirect effects of the 2018 selection, in the main specification of the chapter, I define the treated group as suppliers whose taxable sales to the selected special taxpayers are at least 40% of their total taxable sales in the semester before the selection. The control group consists of suppliers whose taxable sales to large clients that are not selected as special taxpayers are at least 40% of their total taxable sales. Considering the effects on individually owned firms, I find that the output VAT of the treated suppliers decreases by approximately 16.4% (USD 420) while their VAT due decreases by 15.9% (USD 279). If large clients were inflating their costs in coordination with the suppliers before being selected for the program, the observed reductions would indicate a disruption of these cost-inflation practices. The effects on corporate suppliers point in the same direction; however, the results for this group are more suggestive than conclusive due to the presence of pre-trends.

To study the effects of the introduction of withholding between special taxpayers, I exploit variation in treatment intensity along the intensive margin. I compute the ratio of sales to special taxpayers to total sales in 2014 (the year before the reform) and consider the special taxpayers with a ratio above the 75th percentile as the treated group and those with a ratio below the 25th percentile as the control group. I do not find effects on the VAT due, but I find that the reform increased the probability of reporting an unclaimed tax credit after the reform by 25%, going from 57.8% to 72%. Therefore, the reform increased tax revenue temporarily by shifting liquidity from the firm to the government.

Chapter 3 is titled *A Machine Learning Approach to Selecting Large Firms for Tax Monitoring Programs*. In this chapter, I examine whether governments can use machine learning techniques to select firms for large taxpayer programs. These programs target large firms due to their direct contributions to tax revenue through tax liabilities and indirect contributions through withholding (Baer et al., 2002). In line with these goals, I focus on the Special Taxpayers program in Ecuador and use two targets in prediction exercises: the VAT liability of the firm and the VAT that can be observed through the firms (input VAT from non-monitored suppliers).

I train a Random Forest Model and compare its performance to Lasso, Elastic Net, and a simple benchmark model that assigns the mean outcome of the training sample to all observations. The models use data from 2013 to predict outcomes in 2014. I also estimate a pooled specification that combines multiple years, using 2013 features to predict 2014 outcomes and 2014 features to predict 2015 outcomes. I find that the Random Forest model outperforms the other approaches in predicting a firm's VAT liability. However, its performance is weaker when predicting the VAT that can be observed through the firm's network.

Finally, I use the trained model to forecast firms' 2018 VAT liabilities based on 2017 predictors and rank them by their predicted values. Using the number of firms actually selected in 2018 by province, I select the same number of top-ranked firms within each province, based on the predictions. I find that the Random Forest model correctly identifies 57% of the firms that are in the top rank according to their actual VAT liabilities. Future work could refine the predictive models before using them for selecting special taxpayers.

Chapter 1

Third-Party Audits and Firm Behavior: Evidence from a Size-Based Enforcement Policy in Ecuador*

Joint with Andrés Plúas López

Abstract

This paper examines the effects of size-based mandatory audits on firm behavior. We study a reform in Ecuador that reduced the asset threshold above which firms are required to hire an external auditor for financial and tax compliance audits. Using bunching estimation techniques, we find that firms strategically reduce their reported assets to avoid the audit obligation, with asset adjustments explained by changes in current assets. This bunching behavior is not concentrated in industries with low transaction traceability, which suggests that evasion motives are not the main drivers of the response. To assess the effect of audits on firm reporting, we exploit discontinuities around the asset threshold using a donut-hole regression discontinuity design. We find that audited firms report lower costs; however, we do not observe significant effects on corporate income tax liability. These findings suggest that third-party auditors help correct misreporting on the cost side, but have limited effects on revenue reporting, likely because they lack access to third-party information needed to cross-check firms' declared revenues.

* We thank Arthur Seibold, Sebastian Siegloch, Eckhard Janeba, and Davud Rostam-Afschar for their valuable comments and suggestions. We are grateful to the Servicio de Rentas Internas of Ecuador (SRI) for supporting this project. We also thank Christian Chicaiza and Maria Leonor Oviedo from SRI for their assistance with the data and for facilitating research visits to SRI. We are grateful to Segundo Camino Mogro from Superintendencia de Compañías for sharing data on auditors and audited firms. Tania acknowledges funding for research stays from the Center for Doctoral Studies in Economics (CDSE) and Women Go Abroad at the University of Mannheim. We appreciate the research assistance of Katherine Albuja in the final phase of this project.

1.1 Introduction

On average, tax revenues represent 34% of GDP in OECD countries, but only 22% in Latin America and 16% in African countries.[1] Increasing this share is a policy priority for developing countries because higher tax revenue finances public investment (Okunogbe and Tourek, 2024) and reduces the dependence on volatile income sources, such as natural resource rents and foreign aid (Besley and Persson, 2014). To strengthen tax revenue collection, many governments implement size-based enforcement strategies that prioritize monitoring among large firms (Bachas et al., 2019). Although these strategies are widely used, empirical evidence on their effects remains scarce (e.g., Almunia and Lopez-Rodriguez, 2018; Adhikari et al., 2023). To provide new evidence on size-based enforcement, this paper studies a policy in Ecuador that mandates third-party audits of tax returns for large firms.

In Ecuador, firms with assets above a statutory threshold must hire an external auditor to prepare a tax-compliance report submitted to the Ecuadorian Tax Agency (SRI). While third-party financial audits are mandatory for large firms in many countries, Ecuador's regulation adds an extra level of monitoring: the tax compliance report includes a comprehensive review of all items reported in the firm's corporate income tax returns. Auditors are required to identify and report discrepancies between audited accounts and the values originally reported by the firm.

To examine the effects of this enforcement strategy, we study a policy reform introduced in 2016 that reduced the asset threshold used to determine eligibility for third-party audits. Before the reform, firms with assets above USD 1 million in a given year were required to comply with the audit obligation in the following year. Starting in 2016, this threshold was reduced to USD 500,000, requiring firms with assets above this level in 2016 to undergo audits in 2017. The reform expanded the number of audited firms by approximately 6,000.[2]

This institutional setting introduces different monitoring levels and compliance costs around the asset threshold: firms below it are not audited, while those above it face a mandatory audit. We use this setting to examine two behavioral responses. First, we study whether firms bunch below the threshold to avoid the audit obligation. Firms whose cost of adjusting their size is lower than the compliance cost related to the audits may reduce their assets to avoid the audit requirement. Second, we assess how the audit requirement affects tax reporting behavior by comparing audited and non-audited firms located near the threshold. Although the empirical design identifies the effects of being audited relative to not being audited, an important characteristic of this policy is that third-party auditors conduct the audits. We, therefore, interpret the empirical results with attention to this institutional as-

1. These figures are based on the OECD's 2024 Global Revenue Statistics Database.

2. Due to the change in the asset threshold, around 14,000 firms are audited each year (17% of the total number of firms), representing an increase of around 6,000 firms.

pect and discuss the policy implications of relying on third-party auditors for tax enforcement.

Our empirical analysis uses a rich dataset that combines corporate income tax returns from 2013 to 2019 (*Formulario 101*), firm-level characteristics, and links firms to their auditors. We begin by documenting evidence of bunching just below the USD 500,000 threshold. We follow standard bunching techniques based on Kleven and Waseem (2013) and estimate the counterfactual asset distribution that we would have observed in the absence of the policy reform. We find a significant bunching mass of firms below the threshold of approximately four times the number of firms in the counterfactual distribution. While third-party audits of financial statements may bring benefits to firms, such as improved access to credit through certified accounting records (Chen et al., 2016; Baylis et al., 2017), the observed excess mass of firms below the threshold suggests that many firms perceive audits as a net cost rather than a net benefit.

As a placebo check, we examine the asset distribution in 2015, the year before the reform's implementation. We find no significant bunching around the USD 500 thousand threshold, which only became relevant in the following year. In contrast, we observe a clear bunching pattern just below USD 1 million, the threshold in effect at that time. Our estimates indicate that there were five times more firms with assets just below USD 1 million than would be expected in the absence of the audit obligation. This bunching mass disappears once the asset threshold is lowered to USD 500 thousand, which supports the interpretation that firms adjust their asset levels in response to the audit obligation.

We next explore the mechanisms behind the bunching response. Firms can adjust their assets by reducing either their current assets or long-term assets. To identify the adjustment margins, we compute the first differences of the relevant components of assets and liabilities between 2015 and 2016 and examine discontinuities around the asset threshold. We provide evidence that the reduction in assets is mainly driven by an average decrease of USD 60 thousand in current assets. On the liability side of the balance sheet, we find that firms reduce their current liabilities. This pattern suggests that firms are managing short-term liquidity, a response that is expected given that adjustments to more liquid accounts are both less costly and more flexible than restructuring long-term assets. Further, our analysis shows that firms reduce both accounts receivable and accounts payable. This is again consistent with a cash management response to the audit threshold.

The reduction in liquid assets can increase firms' exposure to future shocks. From this perspective, one can interpret the adjustment as a real response due to its potential implications for firm performance, especially in periods of economic distress. Our findings are consistent with a cash management response; however, some of the observed adjustments may also reflect changes in reporting practices rather than changes in economic activity. For example, firms may adjust the timing of payments to suppliers and the collection of payments from clients. To distinguish between real and reporting responses more conclusively, one would need transaction-level data with precise dates for invoices, payments, and collections, as well as information on internal accounting practices.

Next, we assess whether firms with more liquid assets are more likely to bunch. We find that a one percentage point increase in the share of current assets increases the probability of bunching by 7 percentage points. This finding suggests that liquidity is an important constraint on firms' ability to respond to asset-based regulation. Firms with more flexible balance sheets, specifically, those holding a greater share of easily adjustable assets, are better positioned to reduce reported size and avoid audits. Accounting for this heterogeneity is important from a policy perspective, as it suggests that the burden of this enforcement strategy may fall unevenly across firms depending on their asset composition. We also explore whether the asset reform generates extensive margin responses that can affect the bunching estimations, but we do not find any clear evidence of effects on the entry or exit of firms. This suggests that firms mainly respond through balance sheet adjustments rather than more costly strategies, such as shutting down operations.

One may wonder whether the bunching behavior is driven by firms seeking to evade taxes or by firms aiming to minimize compliance costs that go beyond accurate reporting. To better understand firms' motivation, we examine whether bunching behavior differs across industries with different levels of transaction traceability (the share of a firm's sales observed through third-party information). We use traceability as a proxy for the potential ease of evasion since third-party reporting limits firms' ability to underreport income (Pomeranz, 2015; Kleven et al., 2011). When we estimate the bunching response across industries with different levels of transaction traceability, we find no systematic differences in bunching across levels of traceability. This evidence is consistent with firms responding to the compliance costs associated with the audit requirement rather than with evasion incentives.

In the final part of the empirical analysis, we assess the effects of audits on the reporting behavior of audited firms. We compare audited and non-audited firms located near the asset threshold. Because some firms strategically reduce their assets to stay below the threshold and avoid the audit obligation, we cannot implement a standard regression discontinuity design (RDD). To address this issue, we use a donut-hole RDD that excludes firms in the manipulated regions. These regions correspond to the areas where firms accumulate (bunching mass) and where they are missing (missing mass). We identify the boundaries of these regions using the estimates of the bunching analysis. Visually, the bunching begins at an asset level of USD 440 thousand, and the missing mass ends at USD 690 thousand. By excluding firms within this range, we compare those below the threshold, who are not subject to the audit obligation, with those above the threshold, who become audited following the policy reform.

We find that firms just above the asset threshold report 56% lower costs than those just below. However, there is no corresponding effect on reported tax liabilities, possibly due to compensating adjustments in reported revenues. This pattern is consistent with findings from (Carrillo et al., 2017) and (Slemrod et al., 2017), who show that tax enforcement often leads firms to adjust reported costs and revenues. Our results suggest that third-party auditors may be more effective at detecting misreporting in costs than in revenues. Unlike the tax authority, which can cross-check revenue declarations using third-party information, external auditors lack access to such data. Therefore, their audits may have limited effects on tax liabilities. This interpretation supports the idea that bunching is driven by the compliance costs associated with audits, such as the burden of having an external auditor verify every component of the tax return. Even if audits do not change firms' tax liabilities, the perceived hassle, scrutiny, and risk of uncovering errors may still make crossing the threshold undesirable.

The empirical evidence presented in this paper offers three lessons for the design of tax enforcement in developing countries. First, third-party audits improve the accuracy of reported costs, suggesting that delegating certain enforcement tasks to private actors can support the work of tax administrations. This may be particularly useful in contexts where state capacity is limited. However, the absence of effects on reported tax liabilities, combined with offsetting adjustments in reported revenues, indicates that the effectiveness of private monitoring is limited in the absence of third-party information. Thus, the delegation of tax audits contributes to compliance, but cannot substitute for the enforcement capabilities of the tax administration.

Second, the strong bunching response below the asset threshold indicates that firms respond to the compliance burden associated with the audits by adjusting their balance sheets. Our results show that firms use a cash-management strategy, and these financial adjustments can constrain firms' ability to respond to future shocks or finance future investments. The audit threshold may therefore increase monitoring, but also disproportionately burden firms with fewer liquid resources. To address this, policymakers could consider alternative audit assignment mechanisms that are more difficult to manipulate. Further, the tax authority can also increase audit probabilities for firms that bunch below the threshold to discourage the manipulation of reported size.

Finally, the benefits of improved reporting accuracy must be weighed against the costs imposed on firms. These include not only the audit fees but also potential liquidity constraints. If firms reduce liquid assets or delay productive investments to stay below the threshold, the overall impact of this enforcement strategy could be negative.

This paper contributes to the literature that studies the effects of size-based policies on firm behavior (Garicano et al., 2016; Ando, 2021). In the context of taxation, previous research has focused on firms' responses to policy thresholds for the VAT registration (Onji, 2009; Liu et al., 2021; Asatryan and Peichl, 2016), tax notches and minimum tax schemes (Kleven and Waseem, 2013; Best et al., 2015;

Lobel et al., 2024 and Bachas and Soto, 2021), information requirements (Garbinti et al., 2024) and size-based tax enforcement (Bachas et al., 2019; Almunia and Lopez-Rodriguez, 2018; Adhikari et al., 2023). We contribute to this literature by providing new evidence on how firms respond to an asset-based policy. Besides the expected bunching response, we show that firms with more liquid assets are more likely to adjust their size to avoid the audit obligation. Concurrent work by Choudhary and Gupta (2025) studies the elimination of third-party audit mandates in India. In their empirical design, they estimate the compliance effect of audits from the decline in reported tax payments once the audit obligation is lifted. This assumes that firms respond symmetrically to entering and exiting the audit regime. In contrast, the 2016 reform in Ecuador shifts firms from being unaudited to audited, which allows a direct estimate of the effects of mandatory third-party audits without relying on symmetry assumptions.[3]

Our study is related to the research on the participation of the private sector in the provision of public goods and services. While there is rich evidence from other sectors such as education and health (Romero et al., 2020; Banerjee et al., 2019; Galiani et al., 2005), this topic has received less attention in the context of taxation. Recent studies have explored how private agents can support tax collection, for example, by delegating tax collection of indirect taxes to trusted buyers (Garriga and Tortarolo, 2024) or credit card companies (Brockmeyer and Hernandez, 2022) through withholding mechanisms, as well as by involving local elites in property tax collection (Balán et al., 2022). We contribute to this literature by providing novel evidence on the role of third-party auditors and tax compliance. By studying a policy that mandates tax compliance audits, this paper explores whether private actors can cooperate with the government not only as tax collectors but also as monitors of firm behavior.

This paper adds to the extensive literature on taxpayer responses to tax enforcement policies (e.g. Basri et al., 2021; Naritomi, 2019) with a particular emphasis on tax audits. Many studies that explore the effects of audits on taxpayer behavior have relied on randomized audits (Advani et al., 2023; DeBacker et al., 2018; Best et al., 2021), which facilitate the identification of causal effects. However, a more common characteristic of modern tax systems is size-dependent tax enforcement, which targets large taxpayers (Bachas et al., 2019; Basri et al., 2021). Our paper

3. Interpreting the effects of removing third-party audits as equivalent to the effects of being audited has two caveats. First, audits may have already influenced firm behavior, for example, by improving internal controls or changing reporting norms. These effects can persist even after the requirement is lifted. Second, firms may update their beliefs about future enforcement once third-party audits are not mandatory and perceive the probability of being audited as very low, which could amplify the decline in tax payments. Recent evidence from Kotsogiannis et al. (2024) show counter-deterrent effects of some type of audits, where taxpayers report lower taxable income following an audit.

complements this literature by studying a nonrandom audit assignment rule based on asset thresholds.

Finally, a large body of literature studies third-party audits from an accounting perspective. This research has focused on the determinants of audit quality, such as auditor partner tenure and auditor rotation (e.g. Gipper et al., 2017 and Lennox et al., 2014). It also explores the private benefits of audits for audited firms (Chen et al., 2016; Baylis et al., 2017). We contribute novel evidence to this literature by studying the role of auditors in tax compliance.

The remainder of the paper proceeds as follows. Sections 1.2 and 1.3 describe the institutional background and data. We then present our empirical strategy and discuss our results in sections 1.5 and 1.6. Finally, section 1.7 concludes.

1.2 Institutional Setting

1.2.1 Overview of the Ecuadorian Tax System

Ecuador's tax revenue relies on the collection of two taxes: the value-added tax (VAT) and the corporate income tax (CIT).[4] The VAT is charged at a standard rate of 12% with some essential goods and services - such as food and healthcare - qualifying for a zero-rate VAT.

The corporate income tax is levied on a firm's taxable income, which is calculated as the difference between revenues and deductible costs. The tax rate was 22% until 2017, increasing to 25% thereafter. An additional surcharge of three percentage points applies if a firm does not disclose its ownership structure or if a majority shareholder (holding over 50%) resides in a tax haven, low-tax jurisdiction, or preferential tax regime.

1.2.2 Statutory Audits in Ecuador

Large firms in Ecuador are required to undergo a third-party audit of their year-end financial statements. This requirement is based on firm size, a common criterion for audit regulations in other countries, as shown in Table 1.B.1. The Table presents the financial statement audit thresholds across countries of different income levels. We observe that countries use revenues, assets, employment, or a combination of the three as criteria to determine firm size.

The audits in Ecuador have two purposes. First, auditors assess whether a firm's financial statements (balance sheets and income statements) accurately reflect its operations. The results of this assessment are documented in a report submitted to the Superintendency of Companies (Supercias), the government agency responsible

4. Combined, these two taxes accounted for 84% of the total gross tax revenue in 2023 (https://www.sri.gob.ec/historico-estadisticas-generales-de-recaudacion).

for supervising corporate entities in Ecuador.[5] This report includes the certification of the firm's financial statements and the auditor's opinion following the conventions of a regular statutory financial audit.

Second, auditors assess the firm's compliance with tax obligations and prepare a separate report for the Tax Authority (SRI). This tax compliance report documents the discrepancies between the values reported in the tax returns and the audited values. Although the report mainly focuses on corporate income tax returns, it also includes a general review of the currency outflow tax (*Impuesto a la Salida de Divisas*) and the transactions of oil and mining firms.[6]

Supercias sets the asset threshold that determines the audit obligation. Firms with assets exceeding this policy threshold in a given year are required to hire a third-party auditor to review the financial statements and tax obligations for the following year. In 2016, Supercias reduced the asset threshold from USD 1 million to USD 500 thousand, with exceptions for firms with government-owned stakeholders and local branches of foreign companies.[7] The reform was proposed on September 21, 2016, and published in the official gazette on November 11, 2016. Because audit requirements are based on the previous year's assets, firms with assets above USD 500 thousand in 2016 became subject to the audit obligation starting in 2017. There are no additional compliance requirements that change around the asset threshold.

SuperCias authorizes qualified accountants and accounting firms to perform the audits. Authorized auditors meet specific requirements, including holding an accounting or related degree and having a minimum number of years of experience. The authorization granted by SuperCias is valid for three years; after this period, auditors must reapply to renew their status. Firms are responsible for selecting their auditors, but the tenure of an audit partner is limited to five consecutive years.[8] A timeline of the audit process is presented in Appendix 1.D.

1.3 Data

The empirical analysis relies on firm-level administrative datasets from the Tax Agency (Servicio de Rentas Internas, SRI) and the SuperCias. We match firms between the datasets through a unique ID number.

5. Sole proprietorship firms are not regulated by SuperCias and are therefore exempt from this audit obligation.

6. Figure 1.C.2 shows an excerpt from one of the appendices included in the Tax Compliance Report.

7. The relevant asset threshold for firms with government-owned stakeholders and local branches of foreign companies is USD 100 thousand.

8. After the change of the audit threshold, Supercias determined 2016 as the starting year for calculating tenure.

Tax Registry. SRI compiles information on the industry, location, constitution date, and legal form of all firms and sole-proprietorships registered in the Tax Agency.[9] We use the legal form of the firm to identify the taxpayers that are under the supervision of Supercias and subject to tax audits. Specifically, we keep taxpayers classified as limited liability companies, private companies limited by shares, and corporations.[10]

Corporate Income Tax Returns *(Formulario 101)*. We use the corporate income tax returns for years 2013 - 2019 reported by firms to SRI and use the tax registry to select taxpayers with legal forms affected by the change in the asset threshold. We have 576,803 firm-year observations between 2014 and 2019, but we focus on an asset window between USD 100 thousand and USD 2 million, which corresponds to 167,113 firm-year observations. We have information on total assets, current assets, long-term assets, total liabilities, current liabilities, long-term liabilities, equity, revenue, costs, wage bill, income of the exercise, and corporate income tax liability.

Balance sheets and income statements (*SuperCias*). During the first four months of each year, firms are required to submit the balance sheets and income statements for the previous year to the SuperCias, following approval by their shareholders. Since 2015, SuperCias has accepted corporate income tax returns in place of income statements and balance sheets to reduce the reporting burden on firms. While our primary data source consists of corporate income tax returns, we use data from SuperCias to complement the analysis of the disaggregated accounts of current assets and current liabilities.

Auditor-Audited Firm Data. We use a matched auditor-audited firm dataset provided by the SuperCias to explore the compliance effects with the audit obligation. This dataset includes every firm that underwent a third-party audit between 2013 and 2019. Firms can be audited by auditing firms or by individual auditors with relevant academic qualifications (e.g., accountants). Table 1.B.2 shows that the number of auditors has increased since 2017. The number of auditors increased by 29% between 2016 and 2017 and by 13% between 2017 and 2018. The increase in 2018 may reflect the time it takes to be qualified by the Supercias. On average, auditing firms represent 40% of the total auditing agents, though their share has been decreasing since 2016. Additionally, the average number of firms audited by individual auditors increased from 15 before the change in the asset threshold to

9. SRI uses a 6-digit industry code that follows the International Standard Industrial Classification of All Economic Activities (ISIC).

10. These types of firms represent 95% of the total number of firms supervised by SuperCias.

18 after the new asset threshold was set.

Firm-to-firm Transaction Data. Information on transactions between audited firms and auditors and estimates of audit costs can be derived from firm-to-firm transaction data. The data can also be used to analyze heterogeneous responses to the audit obligation, considering information reported by third parties. Since 2012, all formal firms in Ecuador have been required to submit a monthly transactional annex detailing their domestic purchases and sales.[11] However, with the staggered implementation of electronic invoicing in Ecuador, the dataset has gradually lost its representativeness since 2018. SRI provided us with the information from the purchases annex. For each purchase made by a firm, details must be reported, including the supplier's identification, the transaction month, the transaction amount, the VAT paid on the transaction, and the amount withheld from the transaction.[12]

Table 1.1 presents summary statistics. Panel A presents the number of firms located at different points of the asset distribution. Between 2015 and 2016, we observe an increase in the number of firms located in a region close to the USD 500 thousand asset threshold (*bunching region*). In 2015, 1,225 firms reported assets between USD 440 and USD 500 thousand, whereas 2,321 firms reported assets in that range in 2016.

Audit Cost. We estimate annual firm spending on auditing services by merging the firm-to-firm transaction data with the auditor-audited firm data. To calculate this estimate, we aggregate transactions between auditors and audited firms at the annual level. Since the purchases annex lost its representativeness in 2018, we use information from 2017. Following the change in the asset threshold, firms with assets between USD 500 thousand and USD 1 million were required to audit their 2017 balance sheets and income statements, making 2017 the first year affected by the new threshold. These audits were conducted in 2018, with payments likely occurring in the same year. Due to these considerations and the representativeness of the information till 2017, we estimate annual audit spending using 2017 transactions, and focusing on firms with assets above USD 1 million. These audits correspond to the balance sheets and income statements from 2016. In total, 8,220 firms in this group complied with the audit requirement.

11. Sole-proprietorships that keep accounting records and those that do not but report revenues or costs above the thresholds set by SRI are also required to submit the annex.

12. The identifications of clients and suppliers are anonymized and allow us to merge information between different datasets.

Table 1.1. Descriptive Statistics

	2014	2015	2016	2017	2018	2019
Panel A. Number of observations						
Firms	88,350	91,641	94,457	97,210	100,486	104,659
Firms in the main sample (assets between USD 100 thousand and 2 million)	26,275	26,957	27,151	28,045	28,936	29,749
Firms in the bunching region (assets between USD 440 and USD 500 thousands)	1,204	1,225	2,321	2,392	2,466	2,446
Firms in the missing mass region (assets between USD 500 and USD 700 thousands)	3,027	3,074	2,279	2,189	2,261	2,345
Panel B. Summary statistics of main sample						
Yearly average in thousands USD						
Assets	500.71	499.52	493.68	496.89	501.12	499.42
Long -term assets	216.40	217.21	215.14	216.31	216.02	217.46
Current assets	284.31	282.34	278.54	280.58	285.10	281.96
Liabilities	329.33	326.55	320.14	324.32	328.32	327.32
Equity	171.83	181.07	173.81	172.57	172.80	172.10
Revenues	768.00	716.18	645.78	643.96	648.46	630.38
Costs	737.91	692.72	628.45	622.97	628.50	613.21

Figure 1.C.3 presents average audit costs by asset bins in 2017. Firms with USD 1 million assets reported an average annual spending on auditing services of USD 2,706.

1.4 Conceptual framework

Our conceptual framework builds on Almunia and Lopez-Rodriguez (2018), who develop a model to explain firms' responses to increased tax monitoring based on revenue. This model is further adapted by Adhikari et al. (2023) to study corporate responses to an enforcement notch tied to firms' assets.

Third-party audits: Asset-based Enforcement

We describe the firms' size-choice problem under asset-based enforcement with a stylized model. Specifically, we focus on those firms with assets below the old audit threshold that would be audited under a lower, new threshold $\bar{A}$.[13]

Let $A_{t-1} > 0$ denote the firm's level of assets at period $t-1$. In period t, the government reduces the audit threshold to $\bar{A}$. Firms then choose A_t to maximize after-tax profits net of adjustment and audit costs.

The firm produces $\zeta f(A_t)$ units of output, where ζ represents the firm's productivity and $f(.)$ is strictly continuous, increasing, and concave in A_t. The government levies a proportional tax τ on profits, so after-tax profits are

$$(1-\tau)[\zeta f(A_t) - rA_t] \tag{1.1}$$

Adjustment cost

When a firm downsizes (i.e. $A_t < A_{t-1}$), it incurs an adjustment cost $\kappa(A_{t-1} - A_t)$. This cost specification captures the idea that a larger reduction in assets is more expensive.

Audit cost

If $A_t > \bar{A}$, the firm is required to have a third-party audit and pays a cost λ which captures auditor fees and the administrative burden of the audit.[14] Audits can also bring benefits to the firms. For instance, banks may rely on third-party audit reports to assess creditworthiness and issue loans (Chen et al., 2016; Baylis et al., 2017). Thus, we interpret λ as the net cost of the audit obligation that incorporates both its direct costs and potential benefits.

Putting it all together, the firm's problem is:

$$\max_{A_t} \Pi(A_t) \; = \; (1-\tau)[\zeta f(A_t) - rA_t] - \kappa[\max\{A_{t-1} - A_t, \; 0\}] - \lambda[\mathbb{1}(A_t \; > \; \bar{A})] \tag{1.2}$$

We define A_u as the asset level of the marginal firm that is indifferent between downsizing and incurring the audit cost. The indifference condition of the marginal firm is given by:

13. In the conceptual framework, we do not consider the firms with assets above USD 1 million since they are not affected by the reduction of the asset threshold.

14. An extension could allow λ to vary with auditor experience of firm characteristics.

$$\kappa(A_u - \bar{A}) = \lambda \tag{1.3}$$

λ is the net cost of the audit obligation. It equals the auditor's fee plus the compliance burden net of the expected market benefits (e.g., access to credit, market reputation). When these benefits are large enough to offset the direct and administrative costs, firms will choose not to reduce assets to avoid the audit.

We characterize the optimal asset choice, A_t^* as follows:

(1) If $A_{t-1} \leq \bar{A}$, the firm is not audited and has no incentives to downsize. Thus, $A_t^* = A_{t-1}$.

(2) If $\bar{A} < A_{t-1} < A_u$, the firm would be audited. Since the audit cost is larger than the downsizing cost per asset unit, the optimal asset choice is $A_t^* = \bar{A}$. This generates a bunching of firms at the asset threshold. We further assume that the marginal benefit of holding an extra unit of assets up to the audit threshold exceeds the marginal downsizing cost (i.e., $\frac{\partial \Pi(A_t)}{\partial A_t} > 0$) for all $A_t \leq \bar{A}$). Under this assumption, profits are strictly increasing over $[0, \bar{A}]$; therefore, a firm that downsizes to avoid the audit cost will optimally choose $A_t = \bar{A}$.[15]

(3) If $A_{t-1} > A_u$, the cost of downsizing exceeds the audit costs. The firm is audited, and A_t^* is given by $(1-\tau)[\zeta f'(A_t^*) - r] = 0$.

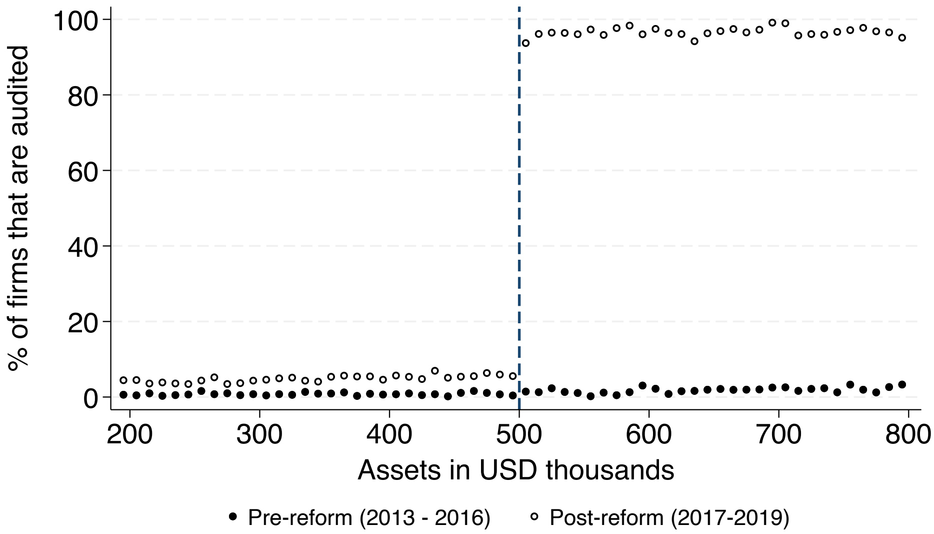
1.5 Bunching Estimation

1.5.1 Compliance with the audit obligation

We first show that firms with assets above the policy threshold comply with the audit requirement. In Figure 1.1, we group firms in USD 10,000 asset bins and show the probability of being audited for each bin in 2013-2016 (pre-reform period) and 2017-2019 (post-reform period). We observe a clear discontinuity in the audit probability of being audited at the USD 500 thousand asset threshold in the post-reform period. At the threshold, the likelihood of being audited increases by approximately 88 percentage points.

15. In our empirical section, we document a very sharp bunching response at $\bar{A}$, which supports this assumption.

Figure 1.1. Audit probability below and above the USD 500 thousand asset threshold



Notes: The figure presents a binned scatter plot showing the share of audited firms relative to the total number of firms in each asset bin for the pre-reform period (2013-2016) and post-reform period (2017-2019). The probability of being audited increases sharply above the threshold; however, compliance with the audit requirement is incomplete. Asset bin size is USD 10,000. Return to the main text.

Compliance with the audit obligation is high and had its lowest level in 2017 (Figure 1.A.1), the first year after the reform of the asset threshold. Compliance rates were 86% in 2017, increasing to 99% in both 2018 and 2019. We also observe a small increase in the percentage of audited firms below the threshold in 2018. This increase can be attributed to the obligation for firms classified as public interest entities (PIEs) to undergo audits.[16] The obligation was first introduced in 2016, but the criteria for classifying a firm as PIE were only defined in 2018. That year, all PIEs were required to be audited regardless of their asset levels. From 2019 onward, only PIEs with assets exceeding USD 500 thousand were subject to the mandatory audits.[17]

The audit obligation results in costs for the firm that go beyond the auditor's fees and may include compliance costs and administrative burdens.[18] Despite these costs, auditing balance sheets and financial statements can bring benefits to firms as mentioned in Section 1.4. If firms perceived the benefits of auditing to outweigh

16. PIES are firms operating in sectors such as insurance and re-insurance, health insurance, third-party auditors, credit rating, construction, real estate activities, vehicle sales, and factoring.

17. Supercias can mandate audits for firms below the threshold in exceptional cases. However, the 2018 increase can be attributed to the obligation for PIEs.

18. The time and effort spent collaborating with auditors to review and adjust the balance sheets and income statements are examples of administrative burdens of the audit obligation.

the costs, we would expect to see a high rate of voluntary audits among the firms. However, as shown in Figure 1.1, this does not seem to be the case: the fraction of firms below the relevant policy threshold that undergo audits is very low. The empirical asset distribution observed in panel a of Figure 1.A.2a further supports the fact that firms perceive the audit obligation as a net cost. In 2016, we observe a bunching of firms just below the new policy threshold of USD 500 thousand, which confirms the efforts of some firms to avoid the audit requirement.

1.5.2 Analysing the bunching response around the asset threshold

Figure 1.A.2a shows the empirical asset distribution in 2015 and 2016. In 2015, the distribution of firms was smooth, around USD 500 thousand, but showed bunching at USD 1 million, which was the relevant audit threshold that year. Following the change in the audit threshold from USD 1 million to USD 500 thousand, the 2016 distribution shows an increase in the number of firms located below USD 500 thousand and a corresponding missing mass of firms above the threshold.[19]

To quantify the bunching response around the policy threshold, we compare the actual density with the density that would have been observed in the absence of the reform (counterfactual density). We use standard bunching techniques around notches as proposed by (Kleven and Waseem, 2013) to estimate the counterfactual density and proceed as follows. We group firms in asset bins of USD 10,000 and regress counts of firms (n_j) in each bin j on a *pth* polynomial of *assets* (Equation 1.4):

$$n_j = \sum_{i=0}^{p} \beta_i (assets_j)^i + \sum_{i=a_L}^{a_U} \gamma_i 1[assets_j = 1] + v_j \tag{1.4}$$

a_L is the lower bound of the bunching region and a_U is the upper bound of the missing mass region. The bunching mass, B, captures the *surplus* of firms located between the asset threshold, a^*, and a_L. This surplus is calculated by comparing the observed distribution of firms to the counterfactual distribution. Algebraically, B is expressed as $\hat{B} = \sum_{j=a_L}^{a*} (n_j - \hat{n}_j)$ where n_j is the actual count, and $\hat{n}_j$ is the counterfactual estimate. Similarly, the missing mass, M, represents the *deficit* of firms observed above the threshold, a^*, compared to the number that would have been observed in the absence of the threshold. This deficit is estimated as $\hat{M} = \sum_{j>a*}^{a_u} (\hat{n}_j - n_j)$. The lower bound a_L is visually identified as the asset level at which firms start to bunch. The upper bound a_U is determined in an iterative process that guarantees that the bunching mass equals the missing mass ($\hat{B} = \hat{M}$).

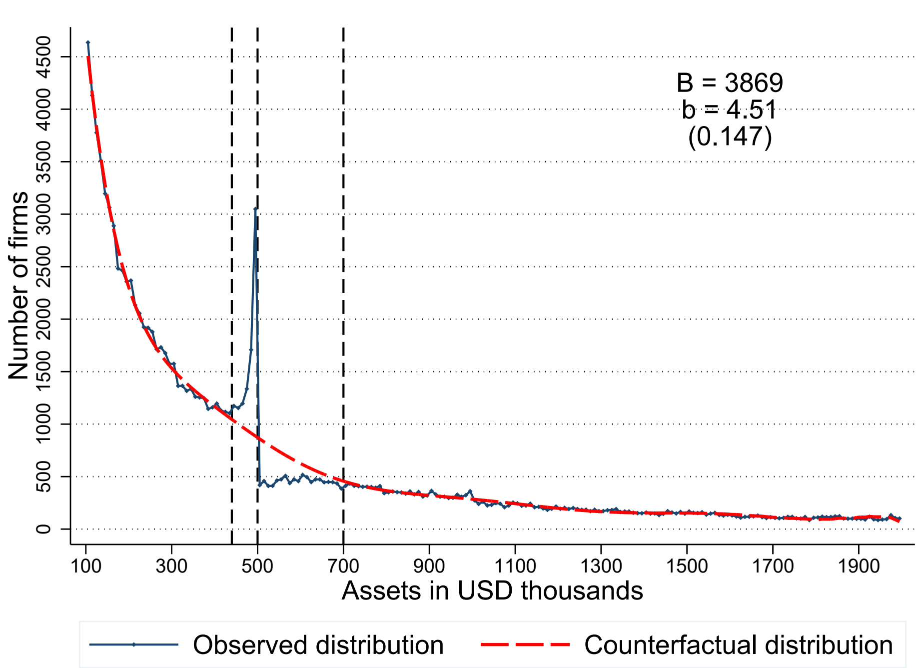
The counterfactual distribution is calculated as the predicted values from equation 1.4, excluding the contribution of the dummies in the area between a_L and a_U.

19. De-bunching in 2016 is not immediate, and we observe a clustering of firms around the USD 1 million threshold in 2016 that disappears in 2017. (Figure 1.A.2b).

Formally, it is expressed as $\hat{n}_j = \sum_{i=0}^{p} \hat{\beta}_i (assets_j)^i$. To facilitate comparisons across different specifications, we normalize B by the average counterfactual distribution in the bunching region (n_0) and obtain the excess mass, $b = \hat{B}/\hat{n}_0$. Standard errors are computed using bootstrapping.[20]

Figure 1.2 shows the asset distribution and the estimated counterfactual distribution around the USD 500 thousand threshold based on a ninth-order flexible polynomial. The data in this figure correspond to a pooled sample from the years 2016 to 2019. The three dashed vertical lines are located at the lower bound of the bunching mass region, the policy threshold, and the upper bound of the missing mass region. Over the 4 years, there are 3,869 more firms located immediately below the threshold, which corresponds to four times more firms than the number we would have observed without the change in the policy threshold ($b = 4.51$). Figure 1.A.3 presents the same exercise conducted by year.

Figure 1.2. Bunching at the USD 500 thousand threshold



Notes: The black dashed lines are located at the limits of the bunching and missing mass regions and at the policy threshold (USD 500 thousand). To construct the counterfactual distribution, we group the firms in asset bins of USD 10,000 and fit a ninth-order polynomial. Return to the main text.

20. Standard errors are estimated using 300 bootstrap samples generated by resampling with replacement from the original residuals.

The bunching behavior observed under the previous asset threshold supports the interpretation that firms react to the audit obligation. To illustrate this, Figure 1.A.4 shows the observed asset distributions and counterfactual distributions during the pre-reform years. Bunching starts at USD 950 thousand, with an average of five times more firms located in the bunching region relative to the counterfactual.

Our estimation of b is robust to changes to a_L, the polynomial order, and the bin size (Table 1.B.3).

1.5.3 Mechanisms behind the bunching response

The observed bunching of firms below the USD 500 thousand threshold may be the result of firms either reducing assets from above the threshold or an increase in firms from below the threshold. To explore these two alternatives, Figure 1.A.5 plots the t-1 asset distribution of firms that reported assets between USD 440 thousand and USD 500 thousand in period t (bunching region). Panel (b) of Figure 1.A.5 shows the 2015 asset distribution for firms that reported assets in the bunching region in 2016. For comparison, panel (a) illustrates the asset dynamics before the threshold reform and presents the 2014 asset distribution of firms in the bunching region in 2015, when the asset threshold was USD 1 million.

The comparison of panels (a) and (b) reveals that although there is an increase in the number of firms entering the bunching region from below the USD 500 thousand threshold, the majority of the bunching can be attributed to firms that had assets above the threshold in t-1. 1,074 of the firms in the bunching region in 2016 reported assets above the threshold in 2015, while only 307 firms in the bunching region in 2015 had assets exceeding USD 500 thousand in 2014.[21]

Firms use a cash flow strategy to reduce their assets. We now study whether the bunching response reflects genuine changes in firm behavior (*real responses*) or adjustments in reporting practices (*misreporting responses*). Boonzaaier et al. (2019) argue that sharp bunching responses are indicative of potential misreporting. While our data exhibit sharp bunching, we further analyze changes in current and long-term assets to determine the type of response.

We compute the first differences in current and long-term assets for each firm and average them within each asset bin. Figure 1.3 shows that firms move below the policy threshold by reducing their current assets. On average, firms just below the threshold reduce their current assets by USD 60 thousand. Although there is an average reduction in long-term assets of USD 11 thousand (Figure 1.4), the overall decline in assets is largely driven by adjustments to current assets. On the

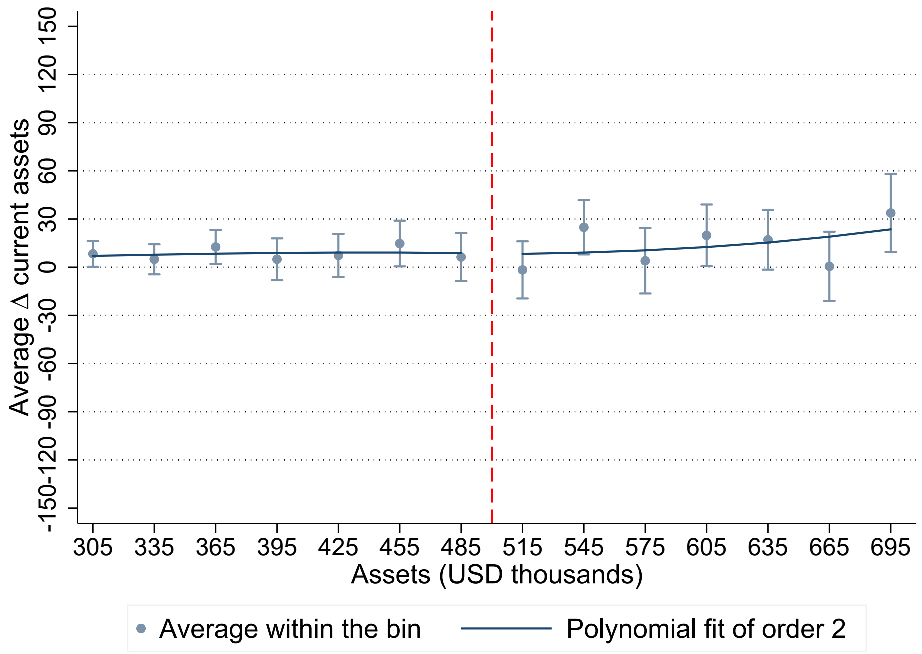
21. 91 firms with assets between USD 900 thousand and USD 1 million in 2015 shifted to the bunching region in 2016. These firms were bunching under the USD 1 million threshold.

liability side of the balance sheets, firms adjust their current liabilities (Figure 1.A.6). Figures 1.A.8 and 1.A.9 further show some evidence that firms reduce their accounts receivable (debts of the clients with the firms) and their accounts payable (short-term debts of the firm with the suppliers) to avoid the audit obligation. It is likely that firms use a *cash flow strategy* to reduce their assets rather than engaging in *real* or *misreporting responses*.

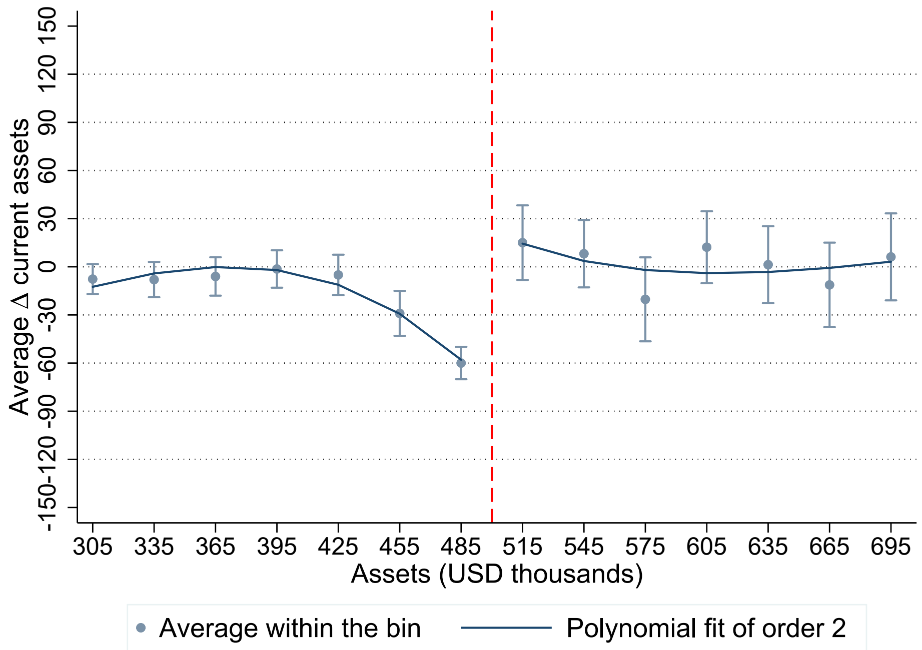
The share of current assets predicts bunching below the threshold. The previous result motivates an analysis of whether firms with a high share of current assets relative to total assets are the ones bunching below the threshold. We start by identifying bunchers as the firms that reported assets between USD 500 thousand and USD 900 thousand in 2015 and reduced their assets to the bunching region in 2016 (i.e., they report assets between USD 440 thousand and USD 500 thousand). Non-bunchers are firms with assets in the same range in 2015 but maintained assets above USD 500 thousand in 2016. We compute the average share of current assets and long-term assets of bunchers and non-bunchers within each asset bin in 2015 and plot the shares in Figure 1.A.10. Firms that bunch below the asset threshold had a higher share of current assets in 2015.

In the next step, we regress an indicator for whether a firm is classified as buncher in 2016 on its pre-reform share of current assets to total assets. Table 1.B.4 presents the results. We include other pre-reform characteristics that may predict the bunching behavior. Firms with more complex accounting records may face a higher administrative burden associated with the audit obligation. To capture this complexity, we include the number and concentration of clients and suppliers as proxies. Across all the specifications, we find a significant correlation between the share of current assets and the probability of being a buncher. Specifically, a 1 percentage point increase in the share of current assets is associated with a 7 percentage point increase in the probability of being a buncher.

Figure 1.3. *Δ* Current assets, t - t-1



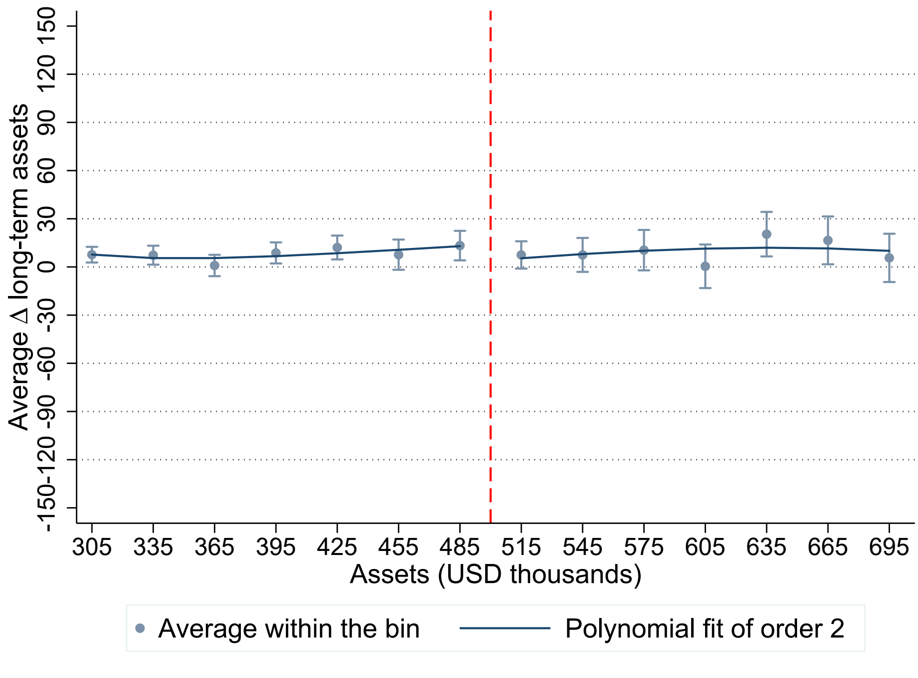
(a) 2015 (pre-reform)



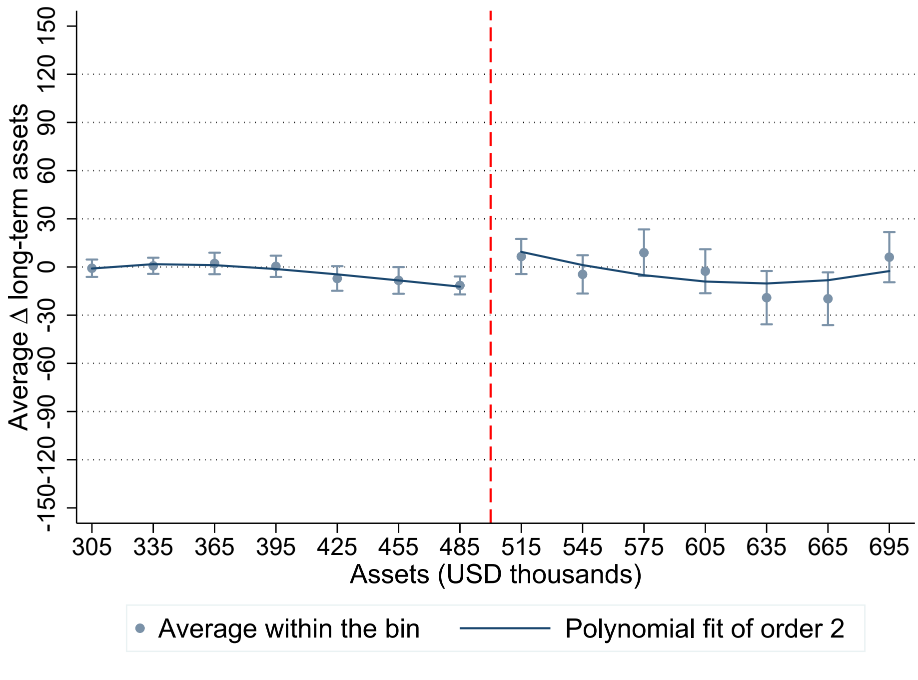
(b) 2016 (post-reform)

Notes: The figure plots the average variation of current assets, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold, and panel b shows the behavior after the reform. Return to the main text.

Figure 1.4. *Δ* Long-term assets, t - t-1



(a) 2015 (pre-reform)



(b) 2016 (post-reform)

Notes: The figure plots the average variation of long-term assets, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold and panel b shows the behavior after the reform. Return to the main text.

Bunching and third-party information. We use third-party information to explore whether bunching behavior is motivated by tax evasion. Previous studies highlight the role of third-party information in tax enforcement (e.g. Kleven et al., 2011). Paper trail has a deterrence effect on tax evasion as shown by (Pomeranz, 2015), who finds that sending messages with the audit probability to taxpayers has a weaker impact on taxes paid by firms that generate more paper trails. In our context, firms may bunch to avoid the audit obligation if they fear that third-party auditors could uncover tax evasion. However, if third-party information deters evasion, firms that produce more paper trails would be less likely to bunch.[22]

To understand whether third-party reporting information plays a role in our context, we follow a similar approach to Almunia and Lopez-Rodriguez (2018) and estimate industry-specific bunching responses. However, instead of using information from input-output matrices, we use firm-to-firm transaction data to compute the traceability of each firm and the average traceability of the industry in 2015 (*pre-reform year*). Traceability is the share of the annual sales that is reported by third parties (local clients of the firms). Table 1.B.5 reports the bunching estimation at the industry level. Manufacturing, wholesale, and retail trade present stronger bunching responses. However, while the sales of the manufacturing sector exhibit the highest traceability, the sales of retail trade present the lowest traceability. It is not clear whether there is a relation between third-party information and bunching behavior in our context. Moreover, we find that these three industries have the highest ratio of current assets to total assets. Conversely, market services have the lowest ratio of current assets and the lowest bunching estimates.[23] This evidence supports the idea that firms with lower asset liquidity, measured through their current asset, bear the burden of the regulation.

Extensive margin responses. The empirical strategy outlined in section 1.5 examines changes in the density mass below and above the asset threshold, assuming that extensive margin responses do not affect the densities (Kleven and Waseem, 2013). Previous studies, such as Harju et al. (2019), have documented extensive margin responses to a size-based policy. To assess if the audit obligation has effects on these margins, we analyze the number of new and closed firms across asset bins around the threshold, comparing data from the pre-reform and post-reform years.

Figure 1.A.11 illustrates the distribution of new firms across asset bins in 2015 versus 2016 (panel a) and 2015 versus 2017 (panel b). The figure further includes

22. The mechanism that we explore is different from Almunia and Lopez-Rodriguez (2018). They argue that third-party information enhances the Tax Authority's ability to detect evasion and thus, firms with more paper trail are more likely to bunch when there is a size-based enforcement policy. Unlike tax auditors, third-party auditors do not have access to third-party information and, therefore, cannot cross-check transactions reported by the audited firm with those of its trading partners.

23. Market services are professional services, administrative services, real estate activities, and information and communication.

the distribution of closed firms in 2015 versus 2016 (panel c) and 2015 versus 2017 (panel d). Although the graphs are descriptive, we do not observe any important changes in the entry or exit of firms that could affect our bunching estimates.

1.6 The Effect of Audits on Audited Firms

1.6.1 Donut-hole regression discontinuity

To assess the compliance effects of the audits, we examine discontinuities in reported variables around the regulatory asset threshold. Following the reform, firms with assets between USD 500 thousand and USD 1 million shifted from being unaudited to audited, while those below the threshold remain unaudited. However, as discussed in Section 1.5, some firms above the threshold reduce their assets to avoid the audit obligation. This strategic behavior prevents the implementation of a standard regression discontinuity design (RDD), as the manipulation of assets violates the continuity assumptions of this research design.

To address this problem, we use the bunching estimates from Section 1.5 to identify the range of manipulation. We define the manipulated region as the interval between the lower bound of the bunching region, a_L, and the upper bound of the missing mass region, a_U. Visually, a_L corresponds to USD 440 thousand, and using the iterative bunching procedure, we find that a_U is USD 690 thousand. Following the approach of Benzarti and Harju (2021) and Bachas and Soto (2021), we drop the firms in the manipulated region and estimate discontinuities at the USD 500 thousand threshold by comparing firms just below the threshold, who are not subject to the audit obligation, with those just above the threshold, who become audited after the policy change.

Figure 1.1 shows that compliance with the audit obligation jumps sharply, but not perfectly, at this threshold. Thus, we instrument audit status in year t with an indicator equal to one if firm $i's$ assets exceed USD 500 thousand in year $t-1$. Then, we estimate the following equations:

$$\begin{aligned} Audit_{it} \;=\; & \rho_0 + \rho_1 \mathbb{1}(assets^d_{i,t-1} \;>\; 0) + \rho_2 assets^d_{i,t-1} + \\ & \rho_3 assets^d_{i,t-1} \mathbb{1}(assets^d_{i,t-1} \;>\; 0) + \mu_{i,t} \end{aligned} \tag{1.5}$$

$$\begin{aligned} log(y_{it}) \;=\; & \alpha_0 + \delta \widehat{\text{Audit}}_{i,t} + \alpha_1 assets^d_{i,t-1} + \\ & \alpha_2 assets^d_{i,t-1} \mathbb{1}(assets^d_{i,t-1} \;>\; 0) + \epsilon_{i,t} \end{aligned} \tag{1.6}$$

where y_{it} is the outcome of firm i in year t and $assets^d_{i,t-1} = assets_{i,t-1} - 500,000$ is the running variable, defined as the distance from the asset threshold. The running variable uses assets from the previous year, since audit status in year t is based on assets reported in t-1. The coefficient of interest is δ, which is the local average treatment effect of the third-party audit on outcome y_{it} for firms whose audit status changed because they are above the threshold. We estimate δ using information from the post-reform years and relying on cross-sectional variation.

We use alternative bandwidths and report the estimated coefficients for all the cases. As a placebo test, we also estimate Equations 1.5 and 1.6 using information from the pre-policy years to verify that the observed discontinuities are explained by the change in the asset threshold.

1.6.2 Third-party audits and tax compliance

In this section, we examine the effects of the third-party audits on the behavior of audited firms. Audits can correct misreporting, and they also help to understand the underlying mechanisms of tax noncompliance, which include the under-reporting of revenues or the over-reporting of costs (Harju et al., 2025). To understand the sources of noncompliance in our setting, our empirical analysis focuses on three key outcomes: reported revenues and reported costs, which are the determinants of the corporate income tax base and the corporate income tax liability itself. Importantly, there were no other policy changes at the USD 500 thousand asset threshold that could confound our results, which guarantees that the estimated discontinuities at the threshold can be attributed to the third-party audits.

As discussed in Section 1.6.1, our objective is to estimate the local average treatment effect at the audit threshold, δ. Figure 1.5 illustrates the discontinuities observed around this threshold by plotting binned averages of reported costs (Panel a) and reported revenues (Panel b), each accompanied by a separate linear trend on either side of the cutoff. We exclude observations located within the bunching and missing mass regions and project the linear trends for those regions. Both panels of Figure 1.5 present jumps at the threshold, particularly for reported costs. This provides preliminary visual evidence indicating that audits influence firms' reporting decisions.

Table 1.2 presents the estimated discontinuities in the key outcomes as specified in Equations 1.5 and 1.6. In particular, column 1 indicates that audited firms reduce their reported costs by 55.7% at the asset threshold.[24]. Additionally, our results also indicate that audited firms report lower revenues, with a decrease of approximately 43.1%.[25] Based on the median values of these variables for a representative firm, third-party audits are associated with a reduction of approximately USD 116 thousand in reported costs and USD 95 thousand in reported revenues.

24. This decrease is calculated as follows: $(e^{-0.814} - 1) \times 100\%$

25. Calculated as $(e^{-0.563} - 1) \times 100\%$.

Although the reduction in revenues is puzzling, a possible explanation for this behavior might be that, in their effort to correct reported costs, audited firms also adjust their revenues to mitigate the impact on tax liabilities. Previous studies have documented that firms often adjust costs and revenues simultaneously in response to increased enforcement. For example, Carrillo et al. (2017) and Slemrod et al. (2017) show that when enforcement targets revenue reporting, firms may respond by also adjusting reported costs to offset any resulting changes in tax liabilities.

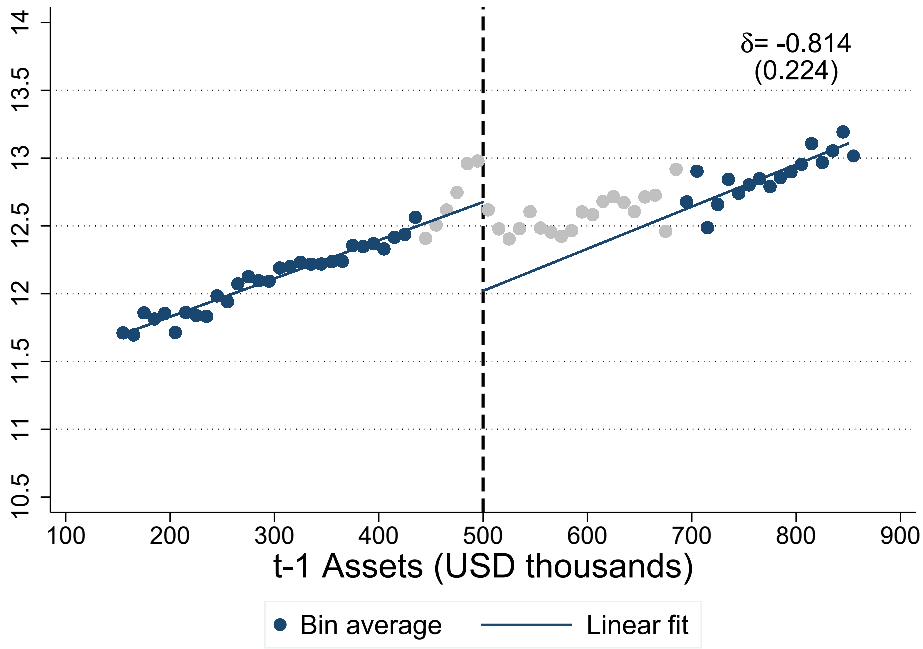
Similarly, Naritomi (2019) finds evidence from Brazil that suggests firms increase reported revenues due to consumer-driven enforcement but partly offset this effect by moderately adjusting reported costs. Thus, our findings are consistent with this literature, highlighting that firms strategically adjust multiple reporting dimensions when faced with an increase in enforcement intensity.

These simultaneous adjustments in reported costs and revenues seem to offset each other. As a result, the net effect on the corporate income tax liability is not statistically significantly different from zero, as shown in Column 3 of Table 1.2. This finding suggests that firms' strategic reporting adjustments neutralize the potential tax effects of the audits.

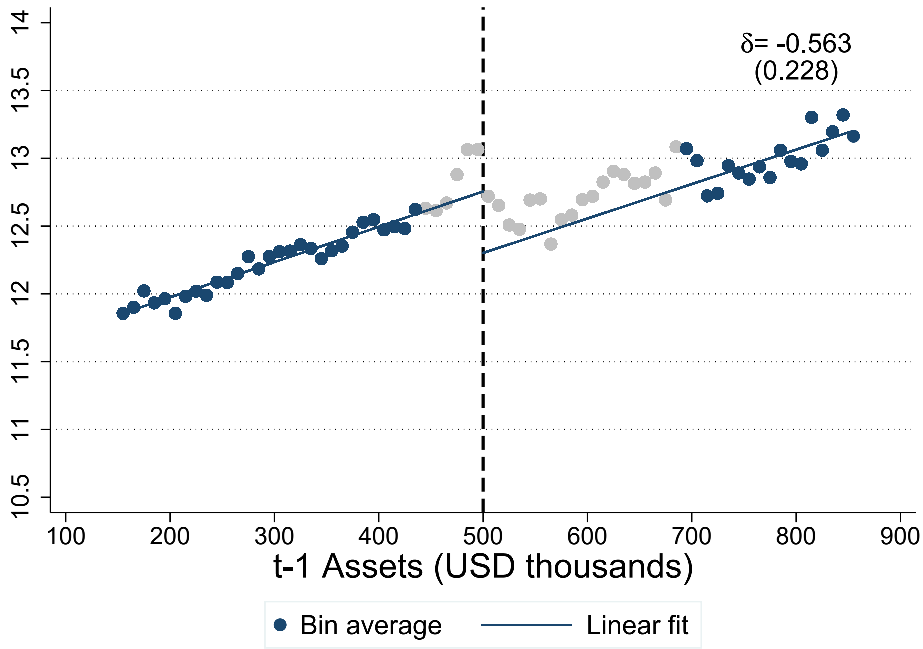
Our RDD estimates rely on a linear approximation of the underlying relation between assets and the reported outcomes. In Figure 1.A.12, we plot the evolution of the outcomes around the USD 500 thousand threshold in the pre-reform years, showing that the relation between assets and outcomes is linear. Moreover, these pre-reform years serve as a placebo test. As shown in the Figure, no discontinuities are observed in the outcomes during this period. Furthermore, Table 1.3 confirms that the estimated discontinuities are not statistically significantly different from zero in the pre-reform years.

Figure 1.5. Compliance effects of audits in the post-reform years

Outcomes in logs



(a) Costs



(b) Revenues

Notes: These figures show discontinuities in reported costs and revenues around the USD 500,000 asset threshold for the post-reform years. The discontinuity, δ, estimated using Equation 1.6, is reported in the upper part of each graph. We also plot the bin averages of the outcomes and the linear fit, which is computed separately for each side of the threshold, excluding the observations in the bunching and missing mass areas. Return to the main text.

Table 1.2. Estimation of outcome discontinuities at the USD 500 thousand asset threshold. Post-reform period

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (3)**
δ	-0.815***	-0.563**	-0.357
	(0.224)	(0.228)	(0.224)
Bandwidth length (USD thousands)	700	700	700
N below	30,256	28,887	23,354
N above	4,127	3,962	3,146
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousand and ends at USD 850 thousand. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Table 1.3. Estimation of outcomes discontinuities at the USD 500 thousand asset threshold. Pre-reform period

Outcomes (logs)	**Costs (1)**	**Revenues (2)**	**CIT liability (3)**
δ	-0.077	-0.071	0.038
	(0.141)	(0.146)	(0.15)
Bandwidth length (USD thousands)	700	700	700
N below	27,187	25,927	21,291
N above	5,011	4,848	3,885
Control Median	404	421	5

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2014 - 2016. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousands and ends at USD 850 thousands. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Robustness Checks.

We conduct several robustness checks to assess the validity of our main estimates. First, we re-estimate the discontinuities using outcome variables adjusted to 2018 prices. As shown in Table 1.B.6, the results remain robust after accounting for inflation.

Next, we assess the sensitivity of our results to the choice of kernel. While our main specification relies on a uniform kernel, which assigns equal weight to all observations, we also estimate the discontinuities using alternative kernels that give more weight to observations closer to the threshold. Table 1.B.7 presents estimates using a triangular kernel, and Table 1.B.8 reports the results under an Epanechnikov kernel. The estimated reduction in reported costs remains between 44% and 45%, while the estimated change in reported revenues is not statistically significant under either specification.

Third, we examine the robustness of our findings to alternative bandwidth choices. Specifically, we modify both the upper and lower bandwidths used in the estimation to restrict the sample to firms located closer to the threshold. Results are reported in Tables 1.B.9 and 1.B.10. Across both bandwidth adjustments, we continue to observe a statistically significant reduction in reported costs. However, the discontinuity in reported revenues is no longer statistically significant when using narrower bandwidths.

1.7 Discussion and Conclusions

In this section, we discuss whether using third-party auditors is a good policy for the government. Evaluating the welfare impact of a traditional audit carried out by tax-agency auditors requires considering the additional revenue generated, the agency's labor costs used for conducting the audit, and the compliance burden imposed on taxpayers (W. C. Boning et al., 2025).

In our setting, however, third-party audits do not generate additional net revenue gains for the tax agency, even though they lead to corrections in reported costs. Private auditors seem to focus on verifying deductions using firm invoices but lack the third-party data needed to validate the reported income. Tax inspectors, by contrast, can cross-match independent reporting sources to uncover under-reported income (Carrillo et al., 2017). This highlights the narrower scope of third-party auditors.

Further, even government-led tax audits can produce unexpected compliance effects when taxpayers update their beliefs about audit risk based on the audit's scope (Kotsogiannis et al., 2024) and its effectiveness (Kasper and Alm, 2022). Although these studies focus on deterrence in subsequent audits, they show that both the scope and efficiency of the audit are important in influencing reporting behavior. In our setting, third-party auditors face a similar narrow scope due to the information at their disposal. These considerations motivate a redesign of third-party audits to improve compliance, as discussed below.

Because third-party audits do not increase a firm's tax liability, one may wonder why firms still bunch below the audit threshold. We now consider the cost side of third-party auditing. One plausible explanation is the costs that these audits impose: our observed bunching behavior seems to reflect firms' efforts to avoid the compliance burden imposed by third-party audits. Like tax-agency audits, third-party audits impose administrative costs on firms (e.g., staff time, data collection), but unlike government audits, they also carry direct fee expenses. Together, these compliance costs and auditor fees create a strong incentive for firms to stay under the audit threshold. This parallels Asatryan and Peichl (2016), who finds that higher compliance costs under stricter accounting rules lead firms to adopt simpler reporting, which reinforces our explanation that compliance burdens can drive bunching.

Since firms themselves pay the fees for third-party audits, auditors face a conflict of interest and may lack the incentives to increase tax revenue collection. Moreover, because private audits do not increase audited firms' tax liabilities, a policy recommendation of this study is to redesign the third-party framework. Duflo et al. (2013) propose two alternatives that change the incentives of auditors in the context of environmental third-party audits in India that could be applied in this context: (1) centralize payments to auditors, and (2) subject auditor reports to random back-checks by the tax agency.

A second policy implication is that government audits could strategically complement private audits. Specifically, the tax authority could randomly audit firms that bunch just below the threshold, where firms seem to be responding to the audit obligation. This approach would raise the expected cost of bunching and reduce incentives to manipulate reported assets.

Finally, by back-checking third-party auditor reports against firms' tax returns and communicating any discrepancies to the auditors, the tax agency can explore whether these communications produce spillover effects among the auditors' clients. If firms learn indirectly about others' audit outcomes, this could amplify deterrence, much like W. Boning et al. (2020) documents audit information diffusing through networks of tax preparers.

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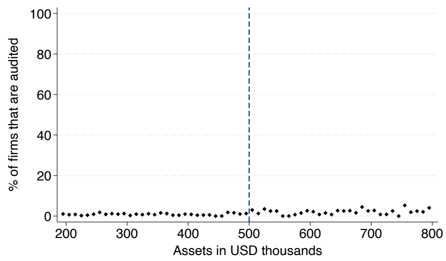
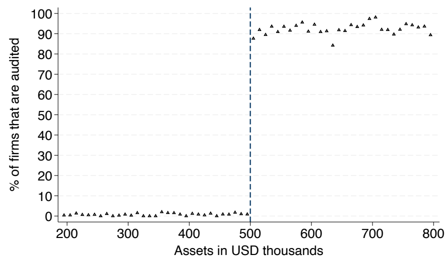
1.A Additional Figures

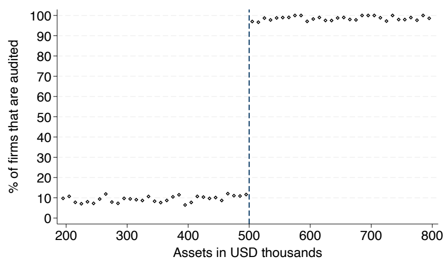
Figure 1.A.1. Audit probability below and above the USD 500 thousand asset threshold per year



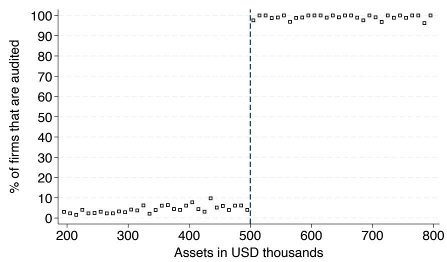
(a) 2016



(b) 2017



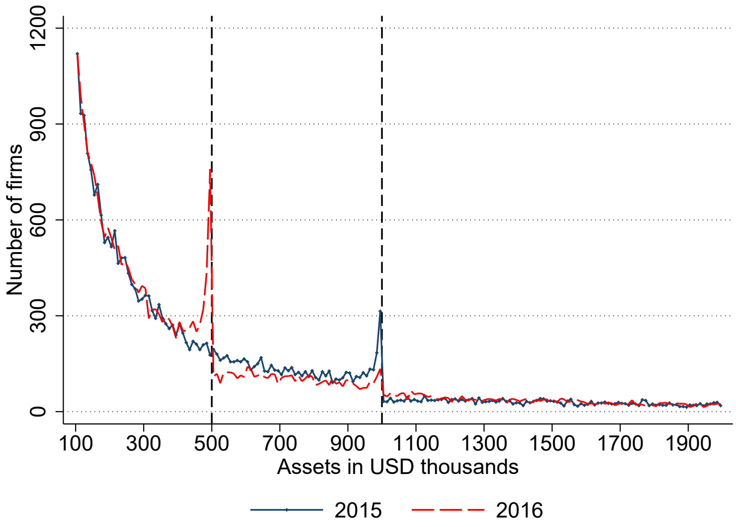
(c) 2018



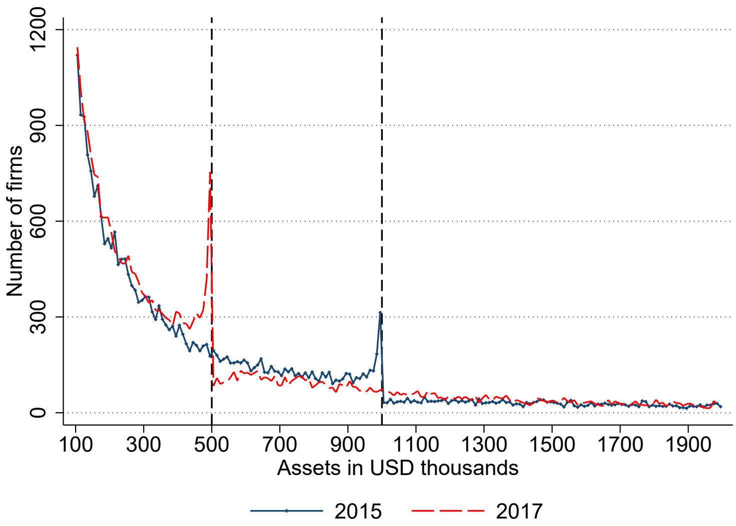
(d) 2019

Notes: These figures plot the share of firms audited within each asset bin, focusing on those near the USSD 500 thousand asset threshold. Panel (a) corresponds to 2016, the pre-reform year when the asset threshold was set at USD 1 million. Panels (b) (c) and (d) illustrate the discontinuity in the share of firms audited around the threshold under the new asset cutoff. Return to the main text.

Figure 1.A.2. Empirical asset distribution



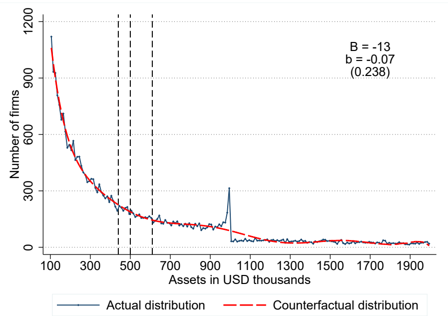
(a) 2015-2016



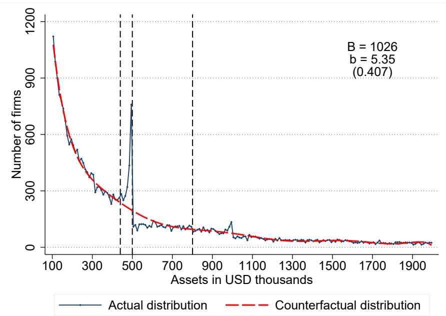
(b) 2015 - 2017

Notes: This figure plots the empirical asset distribution in pre-reform and post-reform years. Panel (a) compares 2015 to 2016 while panel (b) compares 2015 to 2017. The year 2015 serves as a benchmark, showing the distribution under the USD 1 million asset threshold for audit obligations. Return to the main text.

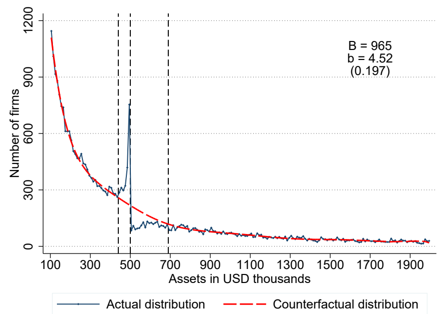
Figure 1.A.3. Bunching at the USD 500 thousand threshold per year



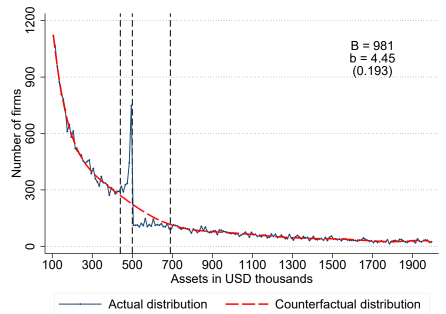
(a) 2015



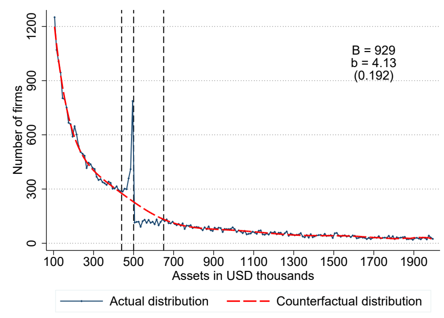
(b) 2016



(c) 2017



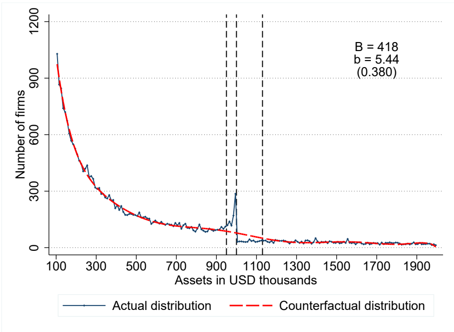
(d) 2018



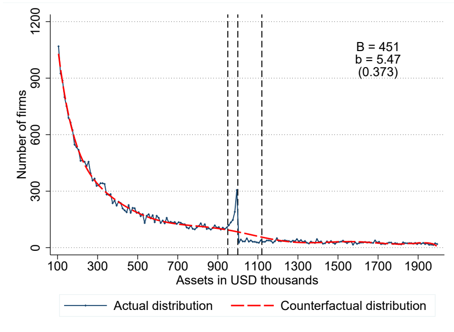
(e) 2019

Notes: These figures plot observed asset distributions (solid lines) and counterfactual asset distributions (dashed lines) for each year. Starting in 2016, there is a sizeable excess mass of firms with assets below the USD 500 thousand threshold. Return to the main text.

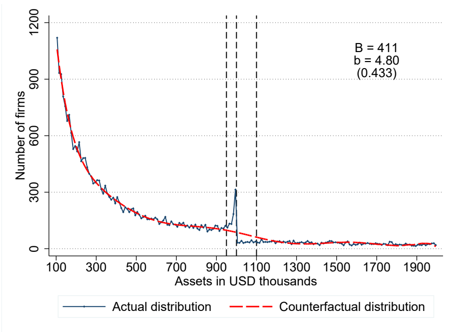
Figure 1.A.4. Bunching at the USD 1 million threshold per year



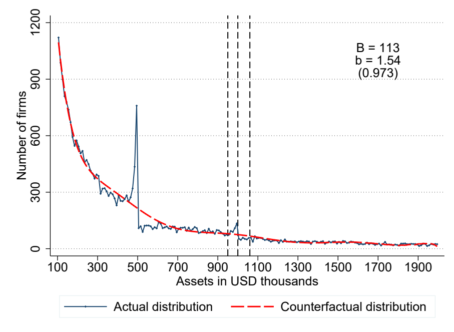
(a) 2013



(b) 2014



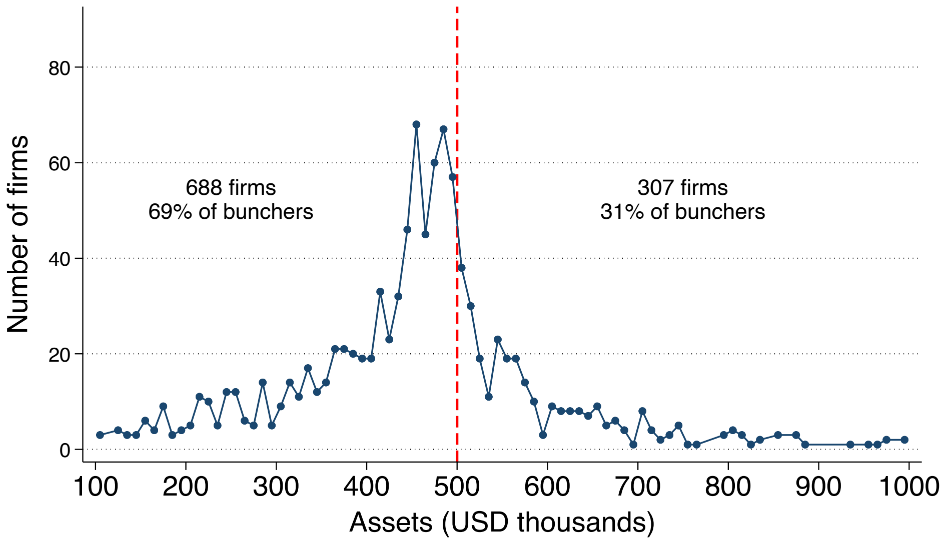
(c) 2015



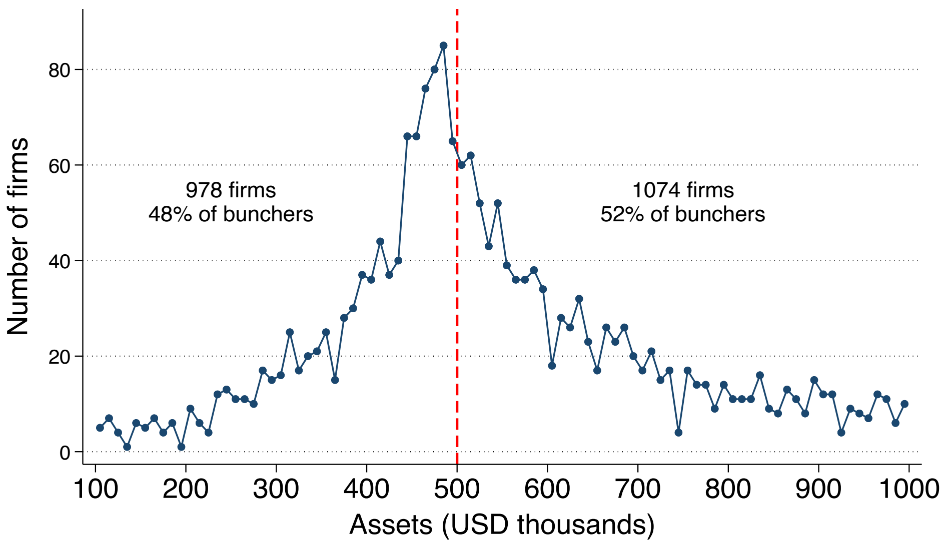
(d) 2016

Notes: These figures plot the observed asset distributions (solid lines) and counterfactual asset distributions (dashed lines) for each year. Before 2016, there is a sizeable excess mass of firms with assets below the USD 1 million threshold. Return to the main text.

Figure 1.A.5. t-1 Asset distribution of firms in the bunching region in t



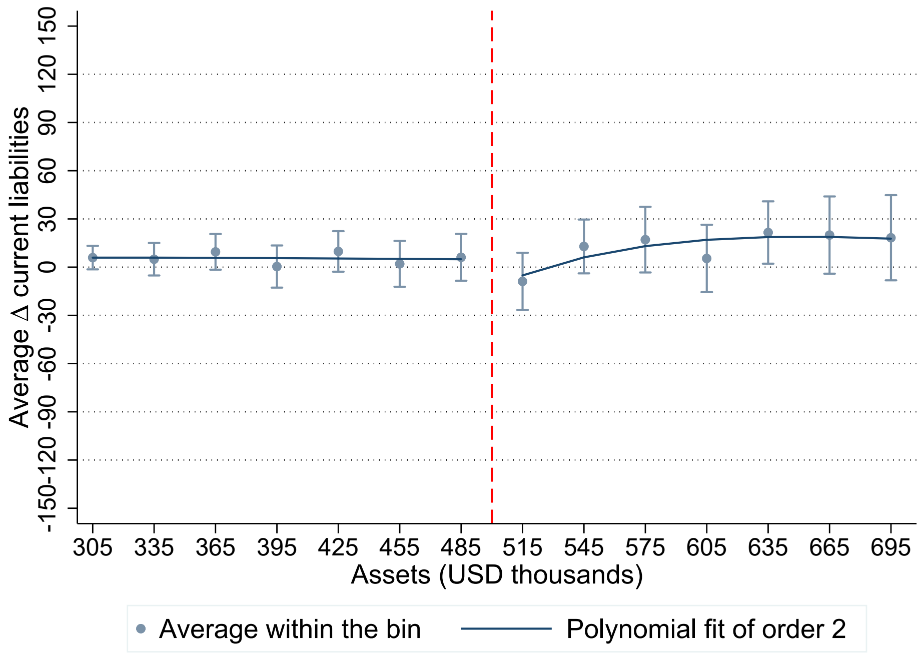
(a) 2015 (pre-reform)



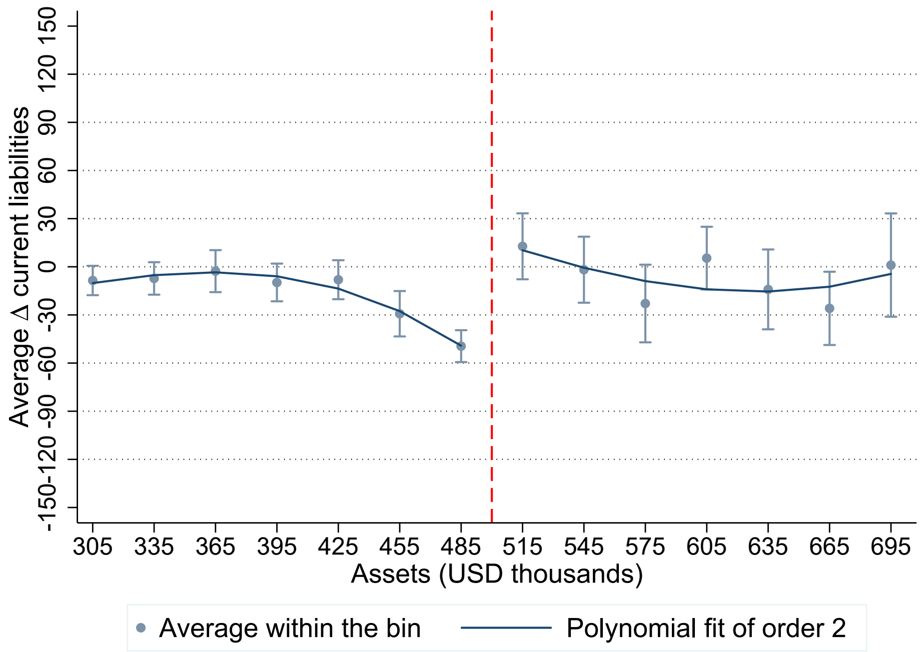
(b) 2016 (post-reform)

Notes: The figure illustrates the asset dynamics around USD 500 thousand before the threshold reform (panel a) and after the reform (panel b). Panel (a) plots the asset distribution in 2014 for firms with assets between USD 440 thousand and USD 500 thousand in 2015. Panel (b) plots the asset distribution in 2015 for firms within the same asset range in 2016. The solid lines of the panels correspond to the observed asset distributions. Firms are grouped into USD 10,000 asset bins. Return to the main text.

Figure 1.A.6. *Δ* Current liabilities, t - t-1



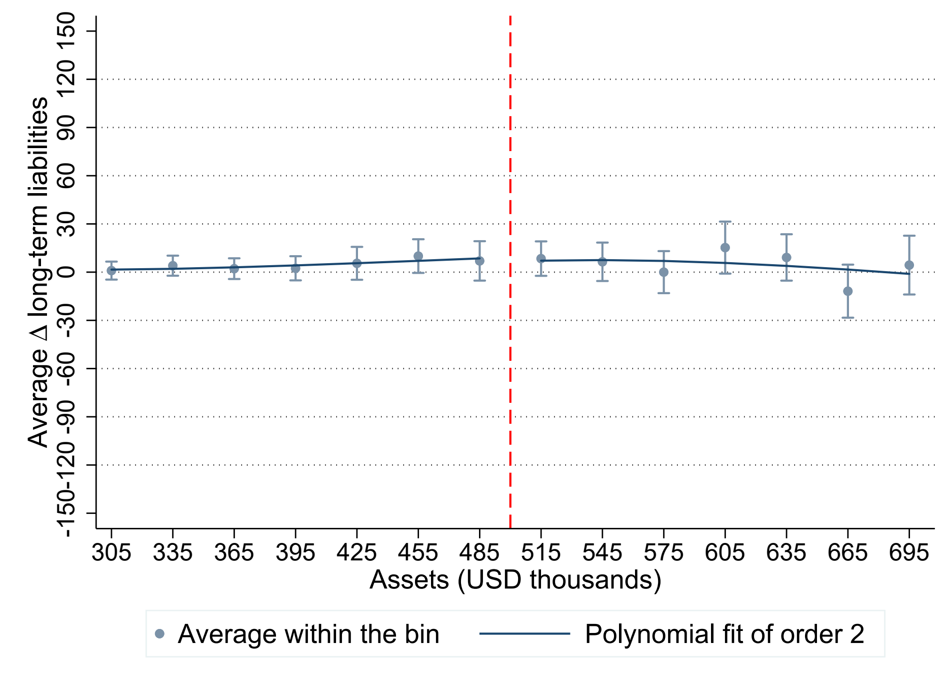
(a) 2015 (pre-reform)



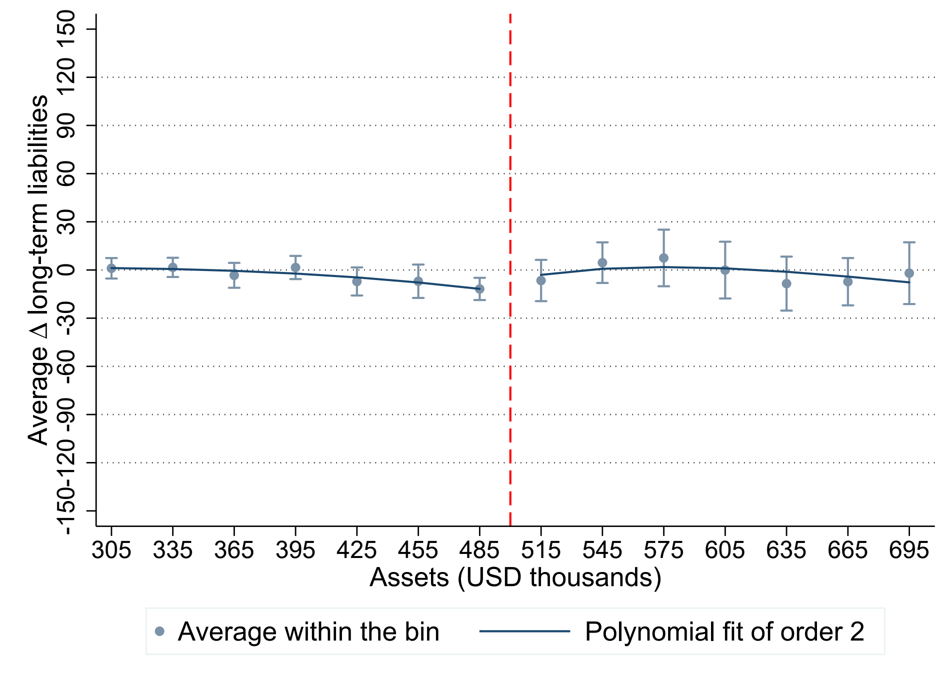
(b) 2016 (post-reform)

Notes: The figure plots the average variation of current liabilities, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold, and panel b shows the behavior after the reform. Return to the main text.

Figure 1.A.7. *Δ* Long-term liabilities, t - t-1



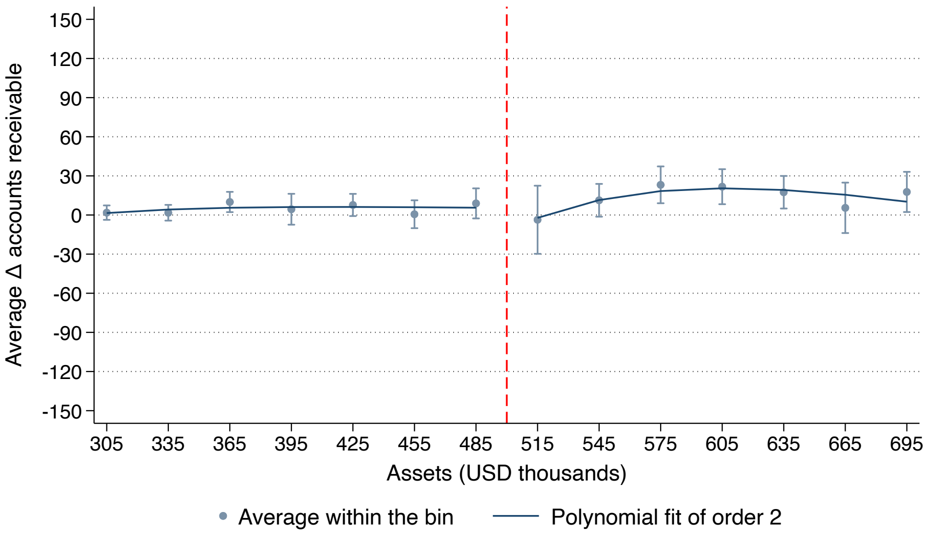
(a) 2015 (pre-reform)



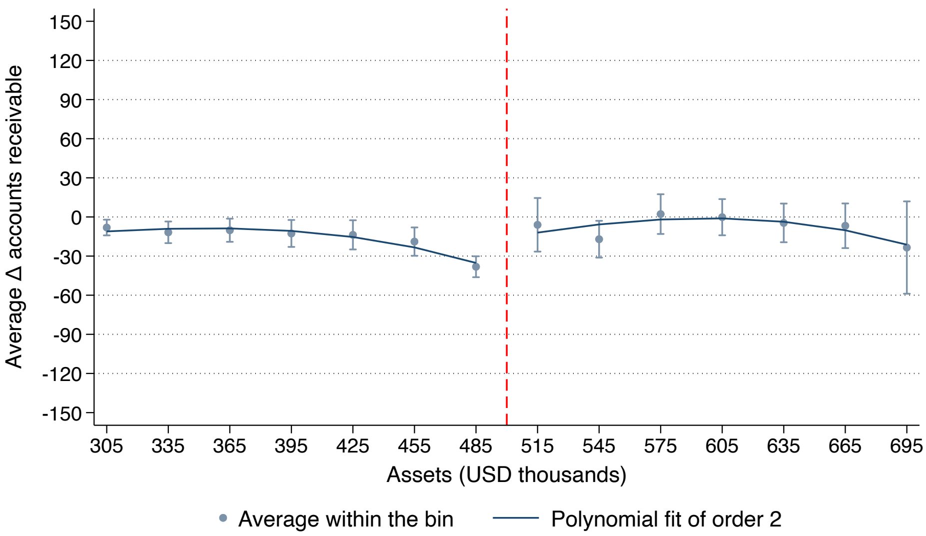
(b) 2016 (post-reform)

Notes: The figure plots the average variation of long-term liabilities, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold and panel b shows the behavior after the reform. Return to the main text.

Figure 1.A.8. *Δ* Accounts receivable, t - t-1



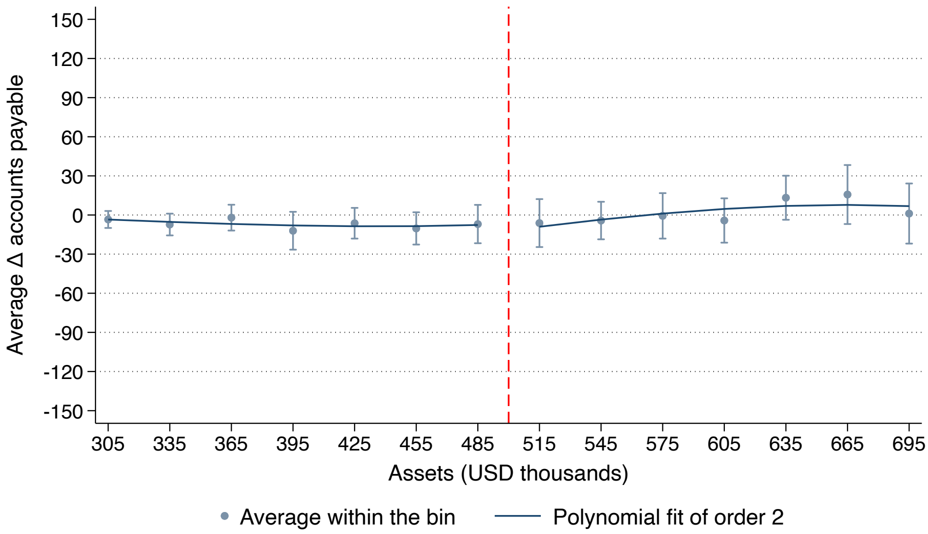
(a) 2015 (pre-reform)



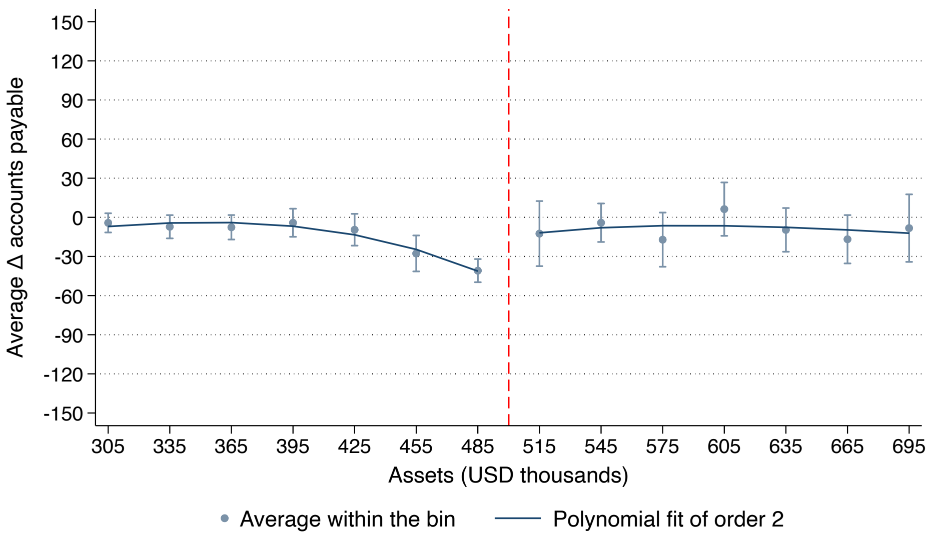
(b) 2016 (post-reform)

Notes: The figure plots the average variation of accounts receivable, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold, and panel b shows the behavior after the reform. Return to the main text.

Figure 1.A.9. *Δ* Accounts payable, t - t-1



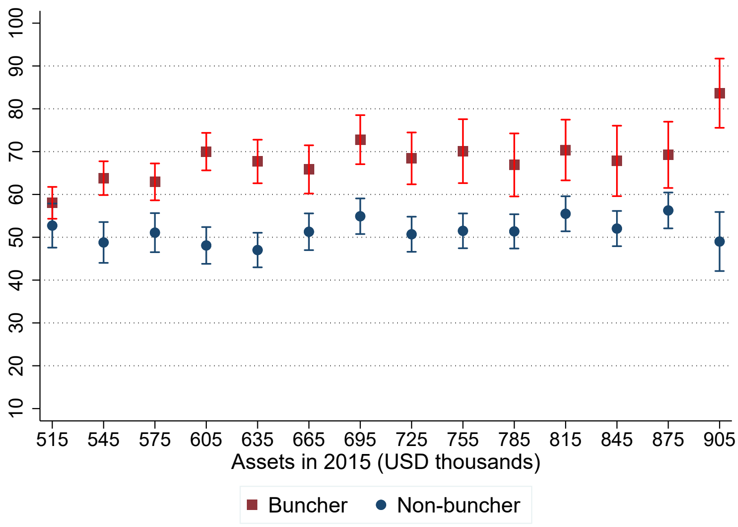
(a) 2015 (pre-reform)



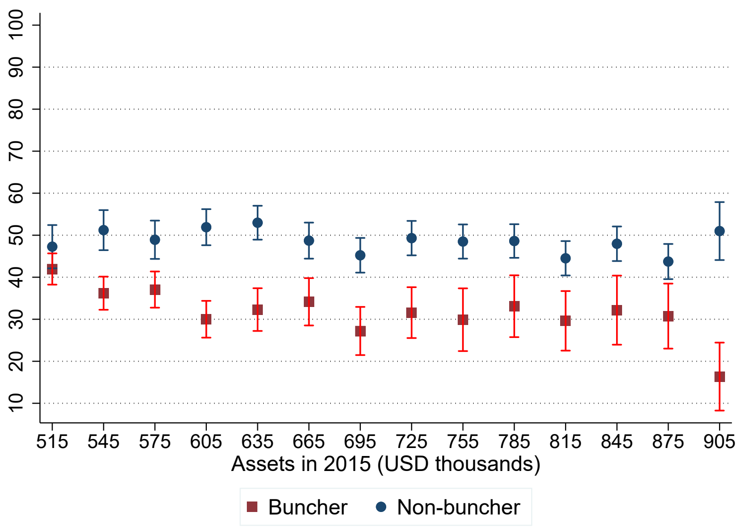
(b) 2016 (post-reform)

Notes: The figure plots the average variation of accounts payable, between 2015 and 2016, for each USD 30,000 asset bin. Panel a shows the behavior before the reform in the asset threshold, and panel b shows the behavior after the reform. Return to the main text.

Figure 1.A.10. Current and long-term assets of bunchers and non-bunchers



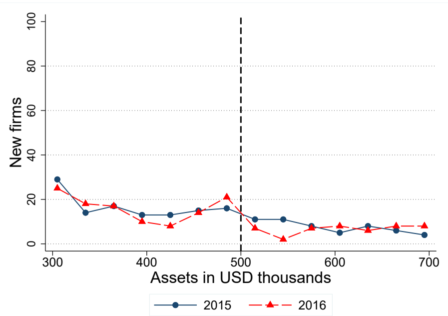
(a) Current Assets



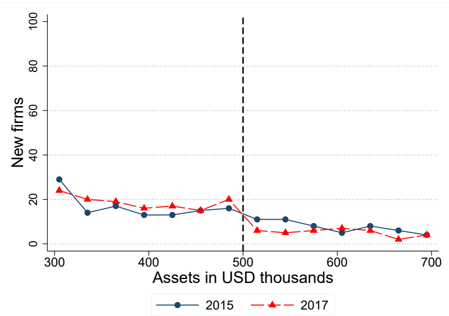
(b) Long-term assets

Notes: This figure shows the composition of current assets and long-term assets as a percentage of total assets for bunchers and non-bunchers. Bunchers are defined as firms with assets between USD 500 thousand and USD 900 thousand in 2015 that reduced their assets and locate in the bunching region in 2016 (i.e. report assets betten USD 440 thousand and USD 500 thousand.). Non-bunchers are firms with assets in the same range in 2015 but maintained assets above USD 500 thousand in 2016. Return to the main text.

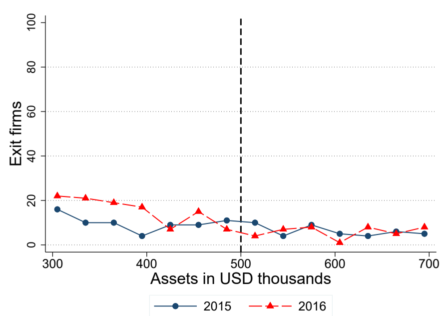
Figure 1.A.11. Firm entry across the asset distribution



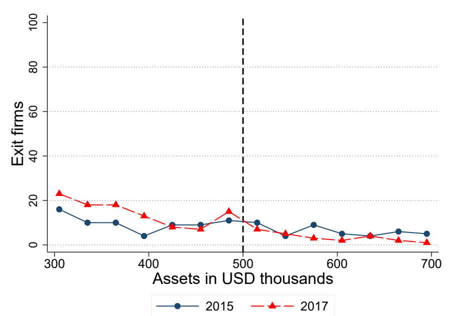
(a) Distribution of new firms, 2015 - 2016



(b) Distribution of new firms, 2015 - 2017



(c) Distribution of closed firms, 2015 - 2016

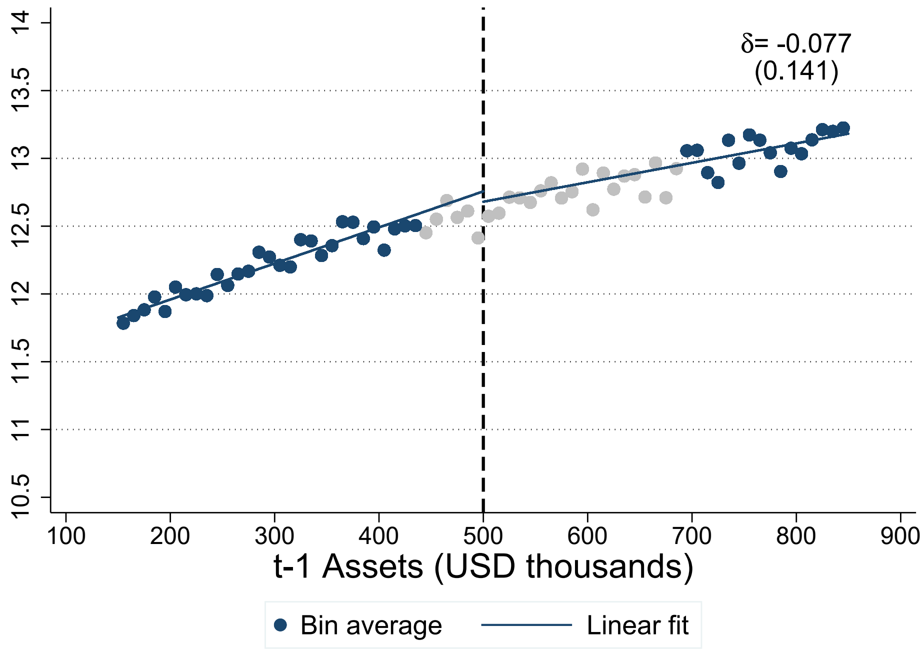


(d) Distribution of closed firms, 2015 - 2017

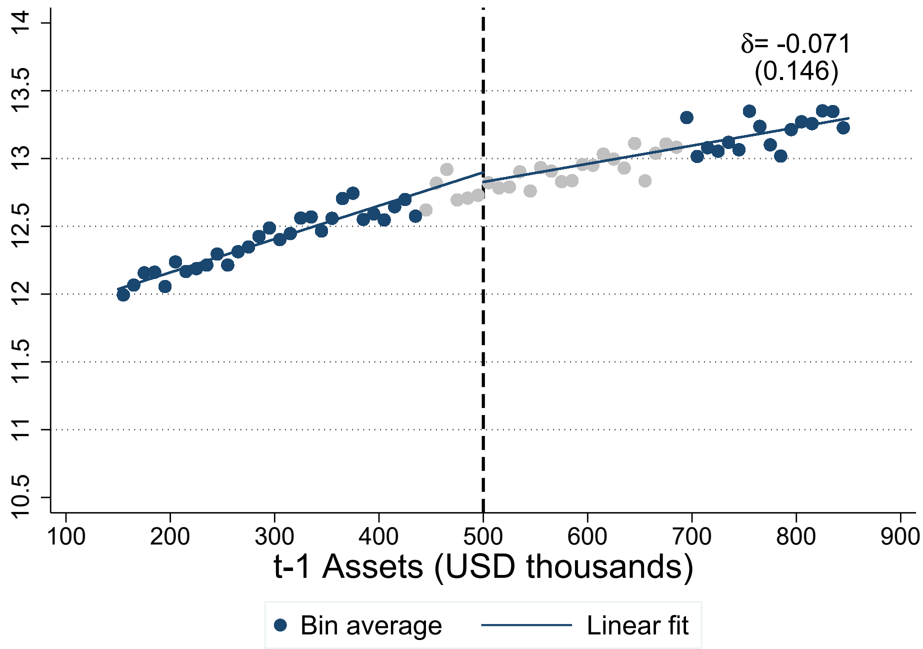
Notes: The figure shows the distribution of new firms in asset bins of USD 30,000 in 2015 and 2016 (panel a) and 2015 and 2017 (panel b). It also shows the distribution of closed firms in 2015 and 2016 (panel c) and 2015 and 2017 (panel d). Return to the main text.

Figure 1.A.12. Compliance effects of audits in the pre-reform years

Outcomes in logs



(a) Costs



(b) Revenues

Notes: These figures show discontinuities in costs, expenses, and revenues around the USD 500,000 asset threshold for the pre-reform years. The discontinuity, δ, estimated using Equation 1.6, is reported in the upper part of each graph. We also plot the bin averages of the outcomes and the linear fit, which is computed separately for each side of the threshold, excluding the observations in the bunching and missing mass areas. Return to the main text.

1.B Additional Tables

Table 1.B.1. Thresholds for statutory audits

Income group	Country	Revenue/turnover/ sales threshold	Asset threshold	Employment threshold	Reference Year
Lower middle income	Cambodia	x	x	x	2024
Lower middle income	Cameroon	x	x		2022
Upper middle income	Colombia	x	x		2024
Upper middle income	El Salvador	x	x		
High income	France	x	x	x	2022
High income	Greece	x	x	x	2024
Upper middle income	Indonesia	x	x		2022
Lower middle income	Haiti	x	x		2020
High income	Italy	x	x	x	2024
Low income	Mali	x	x	x	2022
Upper middle income	Mexico	x			2024
Lower middle income	Morocco	x			2024
High income	The Netherlands	x	x	x	2022
Lower middle income	Senegal	x	x	x	2024
Upper middle income	Serbia	x			2022
High income	Singapore	x	x	x	2023
High income	Spain	x	x	x	2024
High income	Taiwan	x		x	2024
Upper middle income	Türkiye	x	x	x	2024
High income	Uruguay	x			2022

Notes: This table presents the threshold criteria that determine the statutory audit obligation for countries of different income levels. Countries are grouped in income groups using the 2024 - 2025 classification of the World Bank. *Doing business* countries profiles prepared by Deloitte are the source for Colombia, Greece, Indonesia, Mexico, The Netherlands, Serbia, and Uruguay. International Federation of Accountants (IFAC) is the source for Cambodia, Cameroon, El Salvador, France, Haiti, Italy, Mali, Morocco, Senegal, Singapore, Spain, Taiwan, and Türkiye. Return to the main text.

Table 1.B.2. Descriptive statistics of auditors

Year	Number of auditors	Number of auditing firms	Number of individual auditors	Mean number of audited firms by auditor
2013	519	214	305	14.64
2014	554	238	316	14.96
2015	568	248	320	15.43
2016	605	260	345	15.02
2017	783	292	434	15.84
2018	886	330	556	21.22
2019	840	343	497	19.17

Notes: This table presents descriptive statistics of auditors. The number of auditors increases between 2016 and 2017 and 2017 and 2018. Auditors audit 15 firms on average before the change in the threshold and 18 firms after the change. Return to the main text.

Table 1.B.3. Excess mass (b) with different specifications

	$b_{2016-2019}$	b_{2016}	b_{2017}	b_{2018}	b_{2019}
Main specification	4.51	5.35	4.52	4.45	4.13
	(0.147)	(0.407)	(0.197)	(0.192)	(0.192)
Polynomial order= 8	4.29	4.54	4.47	4.27	4.03
	(0.146)	(0.248)	(0.195)	(0.185)	(0.178)
Lower bound (a_L) = USD 450,000	4.27	4.56	4.42	4.14	4.05
	(0.117)	(0.300)	(0.162)	(0.165)	(0.155)
Bin size= USD 9,000	5.70	6.13	5.87	5.66	5.28
	(0.810)	(0.843)	(0.821)	(0.798)	(0.735)

Notes: This table presents the estimates of the excess mass (b) under different specifications and years. To demonstrate the robustness of the bunching estimation, we change the order of the polynomial, the lower bound where the bunching starts, and the bin size. The main specification uses a ninth-order polynomial, a lower bound of USD 440 thousands and bin size of USD 10,000. Return to the main text.

Table 1.B.4. Determinants of bunchers below the USD 500 thousand asset threshold

	Dependent variable: Indicator for whether the firm is a buncher	
Pre-reform characteristics	(1)	(2)
Share of current assets	0.071***	0.072***
	(0.017)	(0.017)
Number of clients	0.00001	
	(0.00001)	
Number of suppliers	0.00002	
	(0.00002)	
Concentration of clients		-0.013
		(0.016)
Concentration of suppliers		0.016
		(0.010)
Industry FE		
N Firms	5,395	5,395
R^2	0.018	0.018

Notes: This table presents the results of the regressions of an indicator for whether the firm is a buncher on pre-reform firm characteristics (corresponding to 2015). Concentration of clients and suppliers is measured using the Herfindahl-Hirschman index. To compute the index, we use firm-to-firm transaction data and calculate supplier's and clients market share. Return to the main text.

Table 1.B.5. Bunching, information traceability and share of current assets

Industry	**N**	**N firms**	**b**	**Mean traceability 2015**	**Current assets as % of assets 2015**
Manufacturing	26,593	4,956	5.87 (0.435)	67	64
Construction	27,707	7,213	3.19 (0.794)	64	60
Market services	94,565	18,290	3.45 (0.222)	62	49
Wholesale trade	64,362	12,931	5.55 (0.323)	56	72
Retail trade	16,918	3,247	6.38 (0.686)	44	71

Notes: This table presents bunching estimates (*b*) by industry, the share of current assets to total assets, and traceability in 2015. Traceability is computed by adding all the transactions reported by third-parties (local clients of the firms) to the Tax Agency and then calculating their share relative to total revenues reported in the VAT returns for 2015. Industries are displayed in descending order based on their traceability level. Market services are professional services, administrative services, real estate activities, and information and communication. Return to the main text.

Table 1.B.6. Estimation of outcomes discontinuities at the USD 500 thousand asset threshold. Post-reform period. Variables at 2018 prices

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (3)**
δ	-0.815*** (0.224)	-0.563** (0.228)	-0.357 (0.224)
Bandwidth length (USD thousands)	700	700	700
N below	30,256	28,887	29,824
N above	4,127	3,962	4,095
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. All variables are transformed to 2018 prices. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousand and ends at USD 850 thousand. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Table 1.B.7. Estimation of outcome discontinuities at the USD 500 thousand asset threshold. Post-reform period. Triangular kernel

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (4)**
δ	-0.575** (0.281)	-0.144 (0.227)	-0.166 (0.277)
Bandwidth length (USD thousands)	700	700	700
N below	30,255	28,886	23,354
N above	4,127	3,962	3,146
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousands and ends at USD 850 thousands. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Table 1.B.8. Estimation of outcomes discontinuities at the USD 500 thousand asset threshold. Post-reform period. Epanechnikov kernel

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (4)**
δ	-0.598** (0.273)	-0.189 (0.272)	-0.186 (0.270)
Bandwidth length (USD thousands)	700	700	700
N below	30,255	28,886	23,354
N above	4,127	3,962	3,149
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousands and ends at USD 850 thousands. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Table 1.B.9. Estimation of outcomes discontinuities at the USD 500 thousand asset threshold. Post-reform period.
Changes in the lower bandwidth

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (3)**
δ	-0.810***	-0.567**	-0.345
	(0.224)	(0.229)	(0.225)
Bandwidth length (USD thousands)	670	670	670
N below	26,938	25,742	20,759
N above	4,127	3,962	3,146
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control group median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 170 thousands and ends at USD 850 thousands. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

Table 1.B.10. Estimation of outcomes discontinuities at the USD 500 thousand asset threshold. Post-reform period.
Changes in the upper bandwidth

Outcomes (logs)	**Costs (1)**	**Revenue (2)**	**CIT liability (3)**
δ	-0.701***	-0.357	-0.333
	(0.263)	(0.229)	(0.265)
Bandwidth length (USD thousands)	670	670	670
N below	30,256	28,887	23,354
N above	3,653	3,505	2,783
Control median (USD thousands)	209	221	1

Notes: This table presents the donut-hole RDD estimates for the discontinuities in the outcomes around the threshold following Equation 1.6, pooling observations from 2017 - 2019. The table reports the bandwidth length (in USD thousands), the number of observations below and above the threshold, and the control median (in USD thousands). The control group median is calculated using observations within the bandwidth range below the threshold. The bandwidth for estimation starts at USD 150 thousands and ends at USD 900 thousands. Standard errors are shown in parentheses. ***, ** and * indicate whether the outcomes are significant at the 1%, 5% or 10% significance level. Return to the main text.

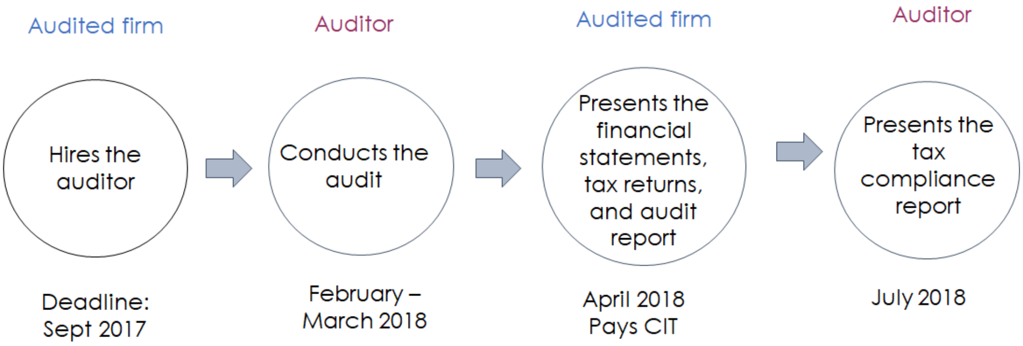
1.C Data Appendix

1.C.1 Variable Definitions

- **Assets.** Sum of current and long-term assets.
- **Current Assets.** It includes all current assets, such as cash, accounts receivable, and inventory.
- **Long-Term Assets.** Non-current assets like tangible assets (e.g., properties) and long-term investments.
- **Current Liabilities.** Short-term debts, including accounts payable, that are paid within one year.
- **Long-term Liabilities.** Obligations that are due for payment in the long run (e.g., bank loans).
- **Revenues.** It is the sum of operating revenues (e.g., sales of goods and services, exports) and other revenues (e.g., income from royalties).
- **Reported Costs.** Sum of all costs and expenses fo the taxpayer.
- **Tax liability.** Corporate income tax liability (25% of taxable profits).
- **Audit cost.** It is computed as the annual amount paid to the auditors and reported in the firm-to-firm transaction data.
- **Traceability.** Traceability is defined as the share of sales of firms that can be observed on the information reported by third parties. The third-party information that we have access to corresponds to the purchases annex, where firms detail all their purchases in a month. We only include the transactions that are categorized as purchases of goods, services, fixed assets, inventories, and health expenses. These transactions correspond to the following codification of tax credit in the purchases annex: 01, 02, 03, 04, 06, 07, and 09. I exclude invoices issued abroad, dividends and rent payments, transactions made by the employees of the firm that are covered by the firm, presumptive withholding, sales receipts issued for the purchases of second-hand cars and movable property, and cash register receipts. These transactions correspond to the following codification of transaction documents: 9, 15, 19, 41, 42, 47, 48, 344, and 364. Finally, I exclude transactions where the client and the supplier have the same tax id. Total sales of a firm are obtained from the Value-Added-Tax returns (*Formulario 104*).
- **Audit cost.** It corresponds to the annual spending in auditing services that a firm reports in the purchases annex. Before computing the annual spending, I exclude the same type of transactions mentioned in the definition of traceability.

1.D Audit process

Figure 1.C.1. Audit timeline



Notes: This figure illustrates the audit process of a firm required to audit the financial statements and balance sheets for 2017. The firm can hire the auditor till September 2017 and must inform Supercias of the auditor's name within 30 days of hiring. The audit is conducted approximately between February and March 2018, following the shareholders' approval of the 2017 balance sheets and income statements. In April 2018, the audited firm presents its financial statements and audit report to the Supercias. Additionally, the firm files its corporate income tax (CIT) returns with the tax authority and pays the CIT in the same month. Finally, in July 2018, the auditor submits the tax compliance report to the Tax Authority.

Figure 1.C.2. Tax compliance report

INFORME DE CUMPLIMIENTO TRIBUTARIO Índice

RAZÓN SOCIAL: COMPAÑÍA XYZ S.A.
RUC: XXXXXXXXXXXXX
EJERCICIO FISCAL: 2018

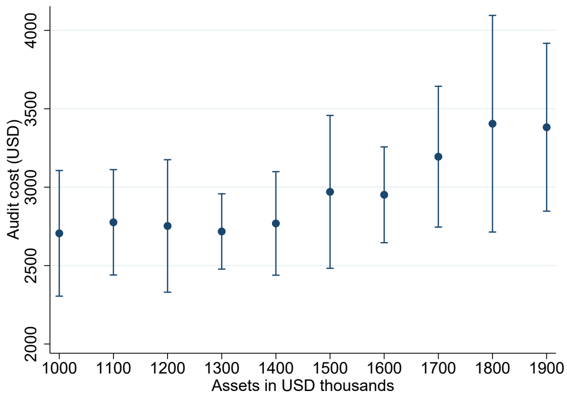
ANEXO No. 4
DETALLE DE LA DECLARACIÓN DE IMPUESTO A LA RENTA

Datos de la declaración del Impuesto a la Renta (a)			Datos de la contabilidad			
Número de Casillero	Nombre del Casillero	Valor declarado	Código de cuenta contable	Nombre de la Cuenta	Valor total del ejercicio fiscal auditado	Diferencias
		{1}	(b)		{2}	{3}={2-1}
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00
		0.00			0.00	0.00

NOTAS :
a. Corresponde al número, nombre y valor del casillero del formulario 101 en el que se efectuó la declaración del impuesto a la renta y presentación de estados financieros para sociedades y establecimientos permanentes. Informar únicamente los casilleros en donde se registraron valores.
b. Los códigos de cuentas deberán ser ingresados al máximo detalle posible, de tal forma que los componentes de cada casillero se puedan identificar claramente.
c. En caso de existir diferencias u observaciones, se debe revelar la explicación de las mismas, tanto al pie de este anexo, como en la parte de Recomendaciones sobre Aspectos Tributarios.

Notes: The Tax Agency publishes the appendices of the Tax Compliance Report on its website. This figure provides an excerpt from one of the appendices, detailing the revision of the corporate income tax. The auditor records the declared value from the corporate income tax return (*Valor declarado*), the audited value for the fiscal year (*Valor total del ejercicio fiscal auditado*), and any discrepancies (*Diferencias*) identified between the two.

Figure 1.C.3. Firm's spending on auditing services



Notes: The figure shows the average spending on auditing services by asset bins and the 95% confidence intervals. The average spending is computed by aggregating all the annual transactions reported by the audited firm in the purchases annex. Return to the main text.

Chapter 2

Upstream Tax Enforcement Mechanisms: Evidence from VAT Withholding and Monitoring of Large Firms in Ecuador*

Abstract

This paper studies how taxpayer programs that increase monitoring of large firms and assign VAT withholding responsibilities affect the behavior of their suppliers. I assess the effects of three policy combinations: (1) indirect effects from the monitoring of large taxpayers, (2) the combined effect of monitoring and VAT withholding, and (3) the introduction of withholding to transactions with monitored suppliers. I find that suppliers whose clients are subject to intensified monitoring reduce their output VAT and VAT due. This result is consistent with a disruption of cost inflation practices that may have benefited large clients before monitoring. I also find that the introduction of withholding between monitored clients and suppliers increases the probability of reporting unclaimed VAT credits.

* I would like to thank Arthur Seibold, Sebastian Siegloch, Eckhard Janeba, and Camila Steffens for their valuable comments and suggestions. I am grateful to the Servicio de Rentas Internas of Ecuador (SRI) for providing access to tax administrative data. I also thank Christian Chicaiza and Maria Leonor Oviedo from SRI for their assistance with the data and for facilitating my research visits. I acknowledge funding for research stays from the Center for Doctoral Studies in Economics (CDSE) and Women Go Abroad at the University of Mannheim. I am also grateful to Katherine Albuja for her excellent research assistance.

2.1 Introduction

Large firms account for a significant share of total tax revenue, with an average of 57% according to Crandall et al. (2021)[1]. Due to their fiscal importance, tax enforcement policies in developing countries often target these firms (Bachas et al., 2019). To improve tax compliance within this group, many governments have established large taxpayer programs, a strategy endorsed by international organizations (e.g., OECD, 2004 and York, 2011). Beyond their direct revenue contribution, large firms play a strategic role for the tax administration because of their connections within supply networks and their responsibility for collecting taxes from their suppliers through withholding mechanisms (Garriga and Tortarolo, 2024). Thus, monitoring large firms not only improves their compliance but may also influence the behavior of smaller suppliers while collecting taxes from them. Since the goal of enforcement policies is to create general deterrence that can affect targeted and non-targeted taxpayers (Slemrod, 2019), understanding the indirect effects on suppliers whose clients are monitored is important to assess the overall impact of these interventions.

There is limited evidence on how tax monitoring affects compliance through supply networks, with the exceptions of Pomeranz (2015) and Almunia et al. (2024). Both studies use experimental variation to assess spillover effects by sending letters that preannounce audits or inform firms of discrepancies in their tax declarations. In contrast, this paper focuses on institutional enforcement mechanisms, specifically the selection of large firms for monitoring programs and the assignment of VAT withholding obligations. An important aspect of this study is its focus on large firms, which typically trade with many suppliers that are connected to only a few clients (Bernard et al., 2019; Alfaro et al., 2018). As a result, enforcement policies targeting large firms may produce compliance spillovers on suppliers.

This paper studies how intensified monitoring of large firms by tax authorities, combined with their VAT withholding responsibilities, affects the behavior of their suppliers. Specifically, I focus on the *Special Taxpayers* program in Ecuador, which combines these two mechanisms. Under this program, large firms in Ecuador are selected for collection and monitoring purposes (SRI, 2009). Large firms in the program are subject to intensified monitoring and withhold the value-added tax (VAT) on transactions with their suppliers. The program also aims to increase the perceived risk of audits for the selected firms and their trade partners (Oliva and Aparicio, 2010).

A client's selection as a special taxpayer affects its suppliers through different channels, which depend on whether the supplier is an individually owned firm (e.g., an entrepreneur) or a corporate firm. For individually owned firms, transactions

1. Figure 2.C.1 presents a map showing the % of revenue collected from large taxpayers by country. Each country defines specific criteria to classify firms as large taxpayers.

with large clients are always subject to withholding, regardless of the client's tax status. Thus, the selection of clients into the special taxpayer program affects this group of suppliers only through monitoring. In contrast, corporate suppliers are affected by both monitoring and withholding. Besides studying the indirect effects of the selection of the clients, I also study a second type of policy that introduced withholding on transactions between special taxpayers. This reform allows me to isolate the impact of withholding in settings where both trade parties are already subject to monitoring.

The study of the indirect effects of tax enforcement strategies on trade partners of targeted firms is limited, mainly due to data constraints. Firm-to-firm transaction data is often scarce or subject to strict access restrictions, making it difficult to observe how enforcement strategies affect the behavior across trade networks. This limitation creates a significant challenge for empirical analysis. To address this challenge, this paper uses rich, detailed administrative tax data from the Ecuadorian Tax Agency (SRI) and exploits policy variation in the Ecuadorian context. An important component of this study is firm-to-firm transaction data, which provides a comprehensive view of the trade networks in the formal sector between 2012 and 2017. Ecuadorian firms are required to submit a monthly purchases annex alongside their Value-Added Tax (VAT) returns (*Formulario 104*).[2] This dataset has information on the anonymized identities of clients and suppliers, transaction values, VAT amounts, and VAT withheld when applicable.

The Special Taxpayer program was introduced in the 1990s, with the selection of special taxpayers initially managed by local tax agencies. Since 2009, however, the process has been centralized under the authority of the national tax agency based in the capital (De Simone, 2022). Since then, there have been three major rounds of selection of new firms: in 2009, 1,189 new firms were designated as special taxpayers; 848 in February 2018, and 1,582 in 2021. This study focuses on the 848 firms selected in February 2018 and identifies their suppliers during the semester preceding their designation.

To quantify suppliers' exposure to the 2018 selection, I compute the share of a supplier's taxable sales to firms designated as special taxpayers in February 2018. This measure is calculated in the semester prior to the clients' inclusion in the program and captures the intensity of each supplier's trade relations with the selected clients. In my main specification, the treated group consists of suppliers whose sales to the selected special taxpayers accounted for at least 40% of their total taxable sales during the pre-selection semester. Suppliers in the control group are those whose taxable sales to non-selected large firms account for at least 40% of their

2. Firms also submit a monthly sales annex. However, this study is based on the purchases annex, as it is the dataset available for analysis.

total sales.[3] I use two types of control clients: (i) large firms that are not special taxpayers, and (ii) large firms selected for the program in 2021. The identification strategy relies on a difference-in-differences setting, and the analysis is conducted at the firm-semester level.

To examine the effects of withholding on special taxpayers, I study a reform in 2015 that extended the withholding regime to include transactions between special taxpayers. Before this reform, these firms were subject to direct monitoring by the tax authority but were not required to withhold VAT from one another. The goal of the reform was to guarantee VAT collection even in transactions between firms already under direct monitoring. To estimate the effect of this reform, I rely on a difference-in-differences strategy that exploits variation in firms' exposure to the policy, measured as the ratio of sales to special taxpayers to total sales in 2014. Treated firms are those with pre-reform exposure above the 75th percentile, while control firms are those below the 25th percentile. The analysis is conducted at the firm-quarter level.

I study two mechanisms through which withholding affects the behavior of suppliers. An increase in output VAT and VAT due would suggest an *enforcement-perception* mechanism (Garriga and Tortarolo, 2024; Brockmeyer and Hernandez, 2022), where suppliers perceive transactions subject to withholding as more likely to be monitored by the tax authority and consequently, they report them accurately. However, an increase in VAT remittances that is reflected in an increase in VAT credits without changes in the output VAT and VAT due would indicate a *default payment effect*: if the amount withheld exceeds the supplier's VAT due and the supplier does not claim a refund, the withheld amount effectively becomes the remitted tax (Brockmeyer and Hernandez, 2022).

An increase in output VAT and VAT due may also reflect *positive spillovers* from the monitoring of large taxpayers. Suppliers more exposed to the 2018 client selection may reduce under-reporting if they had previously evaded taxes, as the perceived likelihood of being monitored increases. In contrast, if suppliers report less output VAT and VAT due, this could indicate that they participated in *cost-inflation practices* that benefit the client before its selection into the special taxpayer program. The intensified monitoring of the clients prevents them from over-reporting their costs and disrupts cost-inflation practices from which they previously benefited.

I now analyze how suppliers respond to the 2018 selection of their clients as special taxpayers. Since the selection affects individually owned suppliers and corporate suppliers differently, I present the results separately. Individually owned suppliers whose share of taxable sales to special taxpayers selected in 2018 represented at least 40% present a reduction in output VAT and VAT due following the clients' selection. Output VAT decreases by approximately 16.4% and VAT due by 15.9%.

3. After I select firms for the treated group, I exclude them from the sample that is used to construct the control groups.

Given a baseline output VAT of USD 2,558, this corresponds to a decline of about USD 420 per semester. Similarly, VAT due decreases by about USD 279 from a baseline of USD 1,753. As discussed earlier, reductions in output VAT and VAT due are consistent with a scenario in which, before the selection, large firms reduce their VAT liability by inflating their costs in coordination with suppliers. Following their selection into the special taxpayer program, the use of these practices is disrupted, and suppliers adjust their reporting.

The effects on output VAT and VAT due are more substantial among more exposed individually owned suppliers. For example, the treated group using a threshold of at least 30% of the total sales to special taxpayers present reductions of 13% in both output VAT and VAT due. Using a threshold of 20%, the reductions are 10% and 9.5%, respectively. Individually owned suppliers were subject to withholding even before the selection of the clients as special taxpayers. Thus, part of their VAT liability was remitted by the large clients, which should prevent some extent of under-reporting of sales from the supplier side. Consequently, the reductions that I observe are more consistent with a form of evasion that benefited the large clients and required the participation of the suppliers to inflate costs.

Corporate suppliers are affected by withholding and the monitoring of the large client. I observe an increase in the VAT withheld after the 2018 selection, which serves as a first stage of the intervention. Further, suppliers' probability of reporting a withholding-related tax credit increases by 34%, from 47% to 63%. Next, when analysing the responses in output VAT and VAT due, I observe that the pre-trends of the outcomes are not very clean. Therefore, the conclusions from this analysis are more suggestive than conclusive. Output VAT and VAT due present decreases after the selection of clients to the special taxpayer program; these responses are not expected when withholding changes the perceptions of enforcement. Instead, they support the existence of cost-inflation practices, as explained before. Further, the absence of an increase in the VAT due and the increase in the probability of reporting a withholding-related tax credit are in line with the hypothesis that withholding operates as a default payment mechanism.

Regarding the introduction of withholding between special taxpayers, I first show that more exposed firms report an average increase of USD 59,130 in the VAT withheld from them after the reform of 2015. Next, I find that the introduction of withholding did not have an effect on VAT due. This result suggests that withholding does not affect compliance behavior once there is monitoring of the client and supplier of the transaction. However, the reform increased the probability of reporting a withholding-related tax credit, which is carried forward to the next period, since firms also have a higher probability of reporting unclaimed tax credits. The probability of reporting an unclaimed tax credit after the reform increases by 25% going from 57.8% to 72%. The effects of unclaimed tax credits indicate that tax revenue can temporarily increase by shifting liquidity from the firm to the government. A back-of-the-envelope calculation suggests that the government holds, on average, USD 115 million in additional unclaimed tax credits. However, these amounts represent temporary cash flow gains for the government, since firms can still use the credits to offset future liabilities, or a refund can be requested.

Considering the two enforcement channels that affect suppliers, monitoring and withholding, the evidence of my study suggests that the indirect effects of the special taxpayer program work through monitoring and particularly by preventing cost-inflation practices that benefited the large clients before their selection as special taxpayers.

Firms selected into the special taxpayers program increase their corporate income tax payments by an average of USD 8,000 (De Simone, 2022). By studying the indirect effects of the program, I provide evidence that over-reporting of costs in transactions with suppliers was part of the evasion strategy of large firms before the selection into the program. This finding helps to understand the overall effects of the program and informs the government about the evasion strategy of large firms.

Finally, introducing withholding between special taxpayers does not have compliance effects but increases the probability of reporting and unclaimed tax credits. The accumulation of these credits reflects a shift of liquidity from the firm to the government and can temporarily increase the tax revenue of the government. Future research could evaluate whether introducing withholding between large firms has effects on their liquidity and performance.

Related Literature and Contributions. This paper contributes to the literature by providing novel evidence on how large taxpayer monitoring programs affect the suppliers of large firms. While previous research has studied the effects of these programs on the compliance of large taxpayers themselves (Almunia and Lopez-Rodriguez, 2018; Basri et al., 2021) and misallocation (Bachas et al., 2019), their effects on the compliance of trade partners remain unexplored.[4] To my knowledge, this is the first study to document enforcement spillovers in the context of large taxpayer monitoring programs.

Two previous studies have analyzed Ecuador's special taxpayer program. Oliva and Aparicio (2010) investigate how the selection of special taxpayers affects their compliance, focusing on a specific region of the country. De Simone (2022) finds that inclusion in the program leads to improvements in firms' financial access and compliance behavior: treated firms pay more corporate income taxes, engage in less evasion, report revenues more accurately, and are less likely to commit accounting fraud. These findings on direct compliance effects provide a compelling motivation to explore whether the program also affects the behavior of firms connected to those

4. Bachas et al., 2019 analyzes more broadly how size-dependent tax enforcement affects misallocation.

under stricter monitoring through firms' networks. Neither study investigates the program's impact on the enforcement of trade connections.

This paper also adds to the literature on networks and tax compliance. Existing papers have analyzed enforcement spillovers among taxpayers connected through tax preparers (Boning and Slemrod, 2018; Battaglini et al., 2023), family ties (Alstadsæter et al., 2019), local networks (Lediga et al., 2023; Drago et al., 2020; Rincke and Traxler, 2011), and workplaces (Bohne and Nimczik, 2025).

Closest to this study are Pomeranz (2015) and Almunia et al. (2024), both of which use experimental designs to analyze compliance spillovers across supply chains. An important distinction is that these studies examine spillovers in settings where evasion is either directly observed or strongly suspected ex ante. Pomeranz (2015) investigates spillover responses to audit announcements communicated through letters, targeting mostly rural and micro-sized firms. Almunia et al. (2024) focuses on spillovers triggered by letters that disclose discrepancies between self-reported and third-party information, explicitly targeting underreporting cases. In contrast, my study analyzes a setting where evasion is not necessarily expected ex-ante. I examine how the selection of large firms for intensified monitoring generates spillover effects on their trade partners. This approach sheds light on how enforcement can propagate indirectly through business networks, even in the absence of direct compliance interventions.

Since special taxpayers are also required to withhold the VAT from their suppliers, this paper is also related to the literature on tax withholding. Brockmeyer and Hernandez (2022), Garriga and Tortarolo (2024), Carrillo et al. (2012) study the compliance effects of withholding in the context of the sales tax in Costa Rica, the turnover tax in Argentina, and the corporate income tax in Ecuador, respectively. Pineda et al. (2024) studies the liquidity effects of VAT withholding in Honduras, where credit card companies are the withholding agents. This paper complements these studies by analyzing a unique policy that extends VAT withholding to large firms, which were previously only responsible for withholding taxes from their suppliers. While firm-withholders are often assumed to comply perfectly, this assumption remains largely unexplored (Slemrod, 2019).

Finally, this paper focuses on the value-added tax and contributes to the literature on the VAT in developing countries (e.g., Brockmeyer et al., 2024 and Mascagni et al., 2021). It also adds to the broader literature on tax compliance of firms in developing countries (e.g., Carrillo et al., 2017; Carrillo et al., 2023; Lobel et al., 2024).

The remainder of the paper is structured as follows. Section 2.2 explains the institutional background. Section 2.3 describes the data sources. Section 2.4 outlines the theoretical background, while section 2.5 presents the research design. The results are discussed in section 2.6. Finally, section 2.7 concludes.

2.2 The Ecuadorian VAT System

The VAT system in Ecuador follows international standards and operates under the invoice-credit mechanism. This means that VAT-registered taxpayers collect the VAT on their sales (output VAT) and issue invoices to clients, who can use them to claim a tax credit or refund against their own VAT liability (Keen and Smith, 2007).

VAT revenue accounts for half of the country's total tax revenue. Goods, services, and imports are taxed at a 12% rate, except for essential goods, which are taxed at a 0%.[5] Taxpayers remit their VAT liability, calculated as the VAT due minus tax credits from previous months, along with the VAT withheld from their suppliers. In 2017, the combined total of VAT payments and withheld VAT amounted to USD 4,806 million.[6] Of this amount, 52% was VAT remitted on behalf of suppliers, which highlights the importance of the withholding mechanism. Further, 85% of the total withheld VAT was remitted by special taxpayers.

Types of taxpayers in the VAT system. SRI categorizes taxpayers into three groups for VAT purposes: special taxpayers, corporate firms, and individually owned firms. Special taxpayers are large firms selected for intensified monitoring and required to withhold the VAT on transactions with their suppliers. The second category is referred as corporate firms and includes two types of firms: (i) individually owned firms that are required to keep accounting records and (ii) corporate firms, which are businesses owned by more than one individual. The third category consists of *individually owned firms*, which are businesses owned by a single individual and are not required to keep accounting records.[7]

Between 2007 and 2019, Ecuador had a simplified tax regime (RISE, *Régimen Impositivo Simplificado*) established to encourage the formalization of small businesses. Firms with fewer than 10 employees and annual sales under USD 60,000

5. Certain goods are subject to a 0% VAT rate, including basic food items (mainly unprocessed food), agricultural goods, medicines, paper, exports, electricity, and electric stoves. Similarly, services taxed at a 0% rate include health care and insurance, education, transport, housing rents, and others. Transactions exempt from VAT do not involve the purchase of goods or the provision of services (e.g., mergers, donations) and are specified in the *Ley de Régimen Tributario Interno*. In April 2016, the Ecuadorian Government temporarily increased the VAT rate to 14% to finance the reconstruction efforts after an Earthquake hit two coastal provinces. This adjustment remained in effect for 12 months, beginning in June 2016.

6. This figure is based on statistics published on the SRI website: https://srienlinea.sri.gob.ec/saiku-ui/.

7. Between 2014 and 2017, the requirement of keeping accounting records depended on the tax-free allowance, which varied annually. For example, in 2014, taxpayers were required to keep accounting records if they met at least one of the following criteria: i. capital above USD 93,690, ii. gross revenues above USD 156,150, or iii. costs and expenses above USD 124,920. A difference between individually owned firms and corporate firms is their tax treatment. The former is subject to personal income tax, which follows a progressive tax schedule, while the latter is subject to corporate income tax (a flat 25% on taxable income, i.e., revenues minus deductible costs). However, VAT rates apply equally to both categories.

could voluntarily register under RISE.[8] RISE allowed the registration of businesses in sectors such as agriculture, fishing, livestock, poultry farming, mining, transport, manufacturing, hotels and restaurants, construction, freelance work, and retail trade. Taxpayers registered under RISE were exempt from charging VAT on sales and could not claim input VAT credits. Instead, they paid taxes based on a progressive tax schedule determined by their sales.

According to the *Directorio de Empresas y Establecimientos* published by the Ecuadorian Statistical Office (*INEC*), Ecuador had 884,236 firms that either reported sales to the tax authority, reported employment to social security, or were registered under the RISE regime in 2017. Of this total, 49% were registered under RISE, 33% were individually owned firms, 14% were corporate firms, and 4% belonged to other categories such as public sector entities and non-profit organizations. This study focuses on firms operating within the VAT system and excludes those in the simplified regime.

2.2.1 VAT withholding

VAT withholding shifts the statutory obligation to remit the tax from the supplier to the client.[9] Figure 2.C.2 illustrates a simple case where a firm (*the supplier*) sells q units of a good to a client. The transaction generates a VAT liability of tq, but instead of the supplier remitting the entire amount, a portion of the tax is remitted by the client, and the remainder by the supplier. In this example, I use a 30% withholding rate, which corresponds to the rate applied to the purchases of goods in Ecuador.[10]

As explained earlier, SRI categorizes taxpayers into three hierarchical levels for withholding purposes: special taxpayers, corporate firms, and individually owned firms. VAT withholding is determined based on this hierarchy. If the client ranks higher than the supplier, the client is required to withhold the VAT from the transaction. Consequently, special taxpayers withhold the VAT from corporate firms and individually owned firms, while corporate firms withhold VAT from individually owned firms.[11] If both parties in the transaction have the same rank, VAT with-

8. In 2020, Ecuador created a second simplified tax regime for microenterprises, RIM. Both RISE and RIM were replaced by another simplified tax regime, RIMPE, in 2022. These regimes were created after the period covered in this study.

9. The correct technical term for this shift in remittance rules is reverse withholding. In the context of VAT, the term withholding is often used to describe the mechanism where firms *prepay* part of the VAT when purchasing from registered suppliers (Keen and Smith, 2007; Waseem, 2022).

10. For simplicity, the example assumes that the supplier does not purchase inputs and, therefore, does not have an input VAT to deduct from the output VAT.

11. During my study period, all corporate firms, regardless of special taxpayer status, were required to withhold corporate income tax. A 2020 reform reassigned this responsibility solely to selected firms and special taxpayers, but this change falls outside the period analysed in this study.

holding does not apply, except in transactions between special taxpayers, which is explained below.[12]

Clients typically withhold 30% of the VAT on purchases of goods and 70% on purchases of services. Table 2.D.1 provides a summary of withholding rates and the transactions subject to withholding. There is no documented explanation for why the withholding rates are set at 30% for goods and 70% for services. It is possible that the SRI aimed to approximate the full VAT liability of suppliers through the amounts withheld by clients. Under this assumption, suppliers of goods would owe VAT equivalent to about 30% of their output VAT, while service providers would owe closer to 70%.

Figure 2.C.3 presents the VAT liability as a ratio of the output VAT across deciles of the sales distribution. Ideally, this ratio should fall below the withholding rates; however, in the case of services, it exceeds 70%. This suggests that the current withholding rate may be too high, potentially leading some firms to accumulate excess tax credits and file for VAT refunds.

The 2015 reform. Until 2014, transactions between special taxpayers were not subject to withholding. This changed with *Decreto Ejecutivo No. 539*, issued on December 31, 2014, which introduced VAT withholding for transactions between special taxpayers. However, the reform did not specify the applicable withholding rates, so special taxpayers initially applied the same rates used for other suppliers: 30% for goods and 70% for services.

The *Resolución No. NAC-DGERCGC15-284*, issued in March 2015, clarified the withholding rates for transactions between special taxpayers. First, withholding between special taxpayers was suspended in April and May 2015. As of June 2015, purchases of goods became subject to a 10% withholding rate, and purchases of services were subject to a 20% withholding rate.

VAT refunds. When the input VAT exceeds the output VAT or when the VAT withheld by clients exceeds the VAT due, the taxpayer reports a tax credit. This credit can be carried forward to the next period. However, if the taxpayers expect that the credit will remain unused for the next six months, they may apply for a VAT refund.

2.2.2 The Special Taxpayers Program

The Special Taxpayers Program was established to monitor large taxpayers and improve tax compliance. The program has four main objectives (SRI, 2009). The first

12. Public institutions, credit card companies, and insurance companies always withhold VAT. Regular exporters and tourism companies have been designated as withholding agents since June 2015. Before this, exporters had to withhold 100% of VAT in some transactions (See *Resolución No. NAC-DGER2008-0124*).

goal is to guarantee tax collection, a central mandate of the tax authority: designated firms are required to withhold the VAT on behalf of their suppliers. Second, tax monitoring is targeted at the taxpayers of the program. Third, the program aims to increase the perceived risk of audits, not only for the selected firms but also for their trade partners. The fourth objective, though less clearly defined, refers to the role of large firms as a source of tax-relevant information. The program seeks to directly influence the compliance behavior of the selected taxpayers while also indirectly affecting their trade partners.

Since the 1990s, Ecuador has designated large firms as part of this program. Initially, the selection process was managed by individual provincial tax offices. However, in 2009, the process was centralized under the main office of the Tax Agency (De Simone, 2022).

The selection criteria capture the taxpayer's economic significance and relevance to Servicio de Rentas Internas, SRI, (Oliva and Aparicio, 2010). Since 2009, the SRI has implemented a new methodology of selection, incorporating variables that reflect the firm size, such as income, costs, and expenses reported in the income tax returns, the sales and purchases reported in the value-added tax returns, and tax withholding (SRI, 2009). For example, in 2010, the selection rule followed this index-based approach (De Simone, 2022) defined as: $Index_{it} = \sum_{s=1}^{3} \phi_s X_{sit-1}$. In this expression, X_{sit-1} represents any of the following three variables (s) for taxpayer i in period t: i. the maximum of reported sales or costs, ii. the total number of taxpayers' suppliers and clients, and iii. taxes owed and withheld by the taxpayer.

Before computing the index, each variable is transformed into a percentile ranking within its respective region. Oliva and Aparicio (2010) point out that SRI uses a threshold to classify the *special taxpayers*, which implies that taxpayers with an index above this threshold were more likely to be selected, though there is also discretion in the selection.

The Special Taxpayer group includes approximately 5,000 firms. There have been three major rounds of new designations: in 2009, 1,189 firms were added to the program; in 2018, 848 new firms were selected; and in 2021, the number of new firms was 1,582.[13] While the total number of special taxpayers remains stable across years, some firms are occasionally suspended from the program.

The selection of a client as a special taxpayer affects suppliers through different channels, depending on their legal form. First, individually owned suppliers were already subject to VAT withholding prior to the client's selection and are therefore only indirectly affected through spillovers from the intensified monitoring of the client. In contrast, corporate suppliers are newly exposed to the withholding regime and are thus affected by both the increased monitoring and VAT withholding.

13. Between 2009 and 2018, the tax agency also carried out smaller updates to the list, selecting an average of 300 new firms per year, except in 2017, when only 3 firms were added.

2.3 Data

2.3.1 Data Sources

I combine several databases from the *Servicio de Rentas Internas* (SRI) using anonimized tax identifiers.[14]

Firm-to-firm transaction data (B2B transaction data). This database contains domestic trade relations between taxpayers in Ecuador's formal sector from 2013 to 2017. The data come from the *Anexo Transaccional Simplificado* (ATS), a monthly purchases annex in which firms report transaction-level information with each supplier. For each transaction, the dataset includes the anonymized tax identifiers of the client and supplier, the month and year of the transaction, the taxable and non-taxable amounts, the VAT amount, any withholding, and the document type.

Using this measure, I construct a measure of *taxable trade* at the client-supplier level, defined as the total value of transactions subject to VAT within a given month. This variable captures the formal trade volume between trade partners and serves as the basis for constructing the exposure measures discussed in Section 2.5.

The SRI introduced the obligation of reporting firm-to-firm transaction data in 2006. Initially, the requirement applied to a narrow group of taxpayers. Coverage expanded in 2008 and again in 2012.[15] Since 2012, the data provide a representative view of trade activity within the formal sector.[16]

Since 2018, firms have no longer been required to report transactions recorded in electronic withholding documents in the purchases annex. Consequently, the data are representative of formal-sector trade only until 2017.[17]

Firm registry and special taxpayers registry. Firms participating in economic activities are required to register in the *Registro Único de Contribuyentes (RUC)*, Ecuador's taxpayer registry. This registry includes information on taxpayer type, geographic location, and industry classification, following the 6-digit ISIC standard classification from the United Nations.

Taxpayers are classified into five categories: individually owned firms (e.g., self-employed individuals), corporate firms in the private sector, public institutions, in-

14. See appendix 2.C.1 for the detailed variable definitions.

15. Initial reporting requirements applied to withholding agents, fund and trust managers, firms using electronic invoicing, and those eligible for VAT refunds. In 2007, the requirement was extended to public institutions, special taxpayers, financial institutions, and credit card companies. By 2012, all firms required to keep accounting records, as well as non-accounting firms above certain revenue or cost thresholds, were obligated to report transactions.

16. The data exclude transactions between firms not required to keep accounting records and those whose revenue or the sum of costs and expenses is below twice the legal threshold for accounting obligations.

17. This change was introduced by *Resolución No. NAC-DDGERGC16-00000092*, issued on February 12, 2015.

ternational organizations (e.g., embassies, cooperation agencies), and taxpayers in the *popular and solidarity economy* (e.g., cooperatives, associations). This registry is used for heterogeneity analysis based on taxpayer type.

The special taxpayer registry includes information on the designation and suspension dates (if applicable), as well as the anonymized tax identifiers. I use this registry to identify designation dates for firms included in the special taxpayers program.

Value-added tax returns. Value-added tax returns are filed monthly, with some exceptions. Semester declarations are allowed in the following cases: i. when the taxpayers exclusively sell VAT-exempted goods or services, and ii. when 100% of the VAT is withheld from the taxpayer. This database contains the tax ID, the year and month of the declaration, sales and exports, output VAT, purchases and imports, input VAT, VAT due (e.g., output VAT minus input VAT), tax credit in the current month, tax credit in the previous month (unclaimed tax credits), VAT withheld by clients, VAT withheld from suppliers, and VAT liability.

2.3.2 Sample selection criteria.

I begin to create the sample for the analysis with the 848 firms that were designated as special taxpayers in February 2018. Public institutions, government enterprises, banks, and credit card companies are excluded from this group. I focus on the 2018 selection because I observe firm-to-firm trade between these firms and their suppliers prior to designation. This allows me to assign suppliers to treatment and control groups based on pre-existing trade relations. Although there were smaller-scale selections of special taxpayers between 2013 and 2016, firms designated during that earlier period were simultaneously implementing electronic invoicing (2014-2016), which has been shown to positively affect compliance (Ramirez-Alvarez et al., 2022). Thus, for those earlier cohorts, I cannot disentangle the effects of special taxpayer designation from those of electronic invoicing.

I then use the firm-to-firm transactions data to construct suppliers' exposure to the selection of special taxpayers in 2018. This measure of exposure is defined as the ratio of taxable trade with clients selected as special taxpayers to the supplier's total taxable sales, as reported in the VAT returns.[18] Exposure is measured using data from the semester before designation, which guarantees that client-supplier links are not affected by the clients' special taxpayer status. To further ensure that suppliers are active prior to treatment, I restrict the sample to those suppliers with sales of at least USD 4,000 in the semester preceding the 2018 selection.[19]

18. Since firms may engage in both VAT-subject and VAT-exempt transactions, I restrict the analysis to transactions that are subject to VAT (*taxable trade*).

19. The median sales reported by individually owned firms before this restriction is USD 5,618.

For comparison, I use two control groups of suppliers that are exposed to trade with large firms that are not designated special taxpayers. *Control Group 1* includes suppliers to large clients that are not special taxpayers.[20]. This group is used in the main specifications. *Control Group 2* consists of suppliers whose exposure is to firms that were designated as special taxpayers in 2021. The treatment and control groups of suppliers exclude taxpayers that are themselves special taxpayers. Further, once the suppliers for the treatment group are selected, they are excluded from the sample used to select the control groups.

To define supplier exposure across treatment and control groups, I use three thresholds: at least 40%, 30%, and 20% of the supplier's total taxable sales. Under a threshold of 40%, for example, a supplier whose sales to special taxpayers selected in 2018 are 40% of total taxable sales is assigned to the treated group. While one might be concerned that suppliers could strategically select clients expected to become special taxpayers, in Section 2.6 I show that there is no evidence of manipulation in the selection process, and the estimates show no pre-trends in the outcomes of interest.

Table 2.1 presents the descriptive statistics for suppliers with exposure above 40% to special taxpayers (*treated suppliers*), to large taxpayers that are not designated as special taxpayers (*control group 1*), and to taxpayers selected as special taxpayers in 2021 (*control group 2*). One can observe that individually owned firms seem to be more comparable across treated and control groups in terms of size and VAT outcomes before treatment. In contrast, corporate firms in the treatment group tend to be larger and report higher taxable sales and VAT amounts than their counterparts in the control groups.

Table 2.B.1 reports the same statistics for the 30% exposure threshold, and Table 2.B.2 presents them for the 20% exposure threshold. For the analysis, I aggregate the data at the semester level, since some small taxpayers report at this frequency.

20. To define a large client, I follow the official classification of medium-sized firms and identify suppliers of firms with annual sales exceeding USD 1 million.

Table 2.1. Descriptive Statistics. 40% Threshold

All variables expressed in 2018 USD (thousands)
Second semester of 2017

	Panel A. All suppliers					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	76.96	(306.04)	44.47	(139.55)	48.55	(189.62)
Taxable purchases	52.11	(265.60)	27.18	(112.47)	28.73	(133.65)
Output VAT	9.23	(36.73)	5.34	(16.75)	5.83	(22.75)
Input VAT	6.25	(31.87)	3.26	(13.50)	3.45	(16.04)
VAT due	4.88	(15.88)	3.02	(8.74)	3.33	(13.28)
Observations	4,412		19,693		4,039	

	Panel B. Individually owned firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	23.75	(28.40)	21.32	(28.50)	21.33	(29.77)
Taxable purchases	9.96	(19.50)	8.97	(22.04)	8.95	(20.37)
Output VAT	2.85	(3.41)	2.56	(3.42)	2.56	(3.57)
Input VAT	1.20	(2.34)	1.08	(2.64)	1.07	(2.44)
VAT due	1.95	(2.44)	1.75	(2.42)	1.77	(2.46)
Observations	3,310		15,742		3,194	

	Panel C. Corporate firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	237.24	(582.74)	137.42	(289.36)	153.29	(396.30)
Taxable purchases	178.85	(510.67)	99.66	(234.01)	103.26	(278.80)
Output VAT	28.47	(69.93)	16.49	(34.72)	18.39	(47.56)
Input VAT	21.46	(61.28)	11.96	(28.08)	12.39	(33.46)
VAT due	13.70	(29.87)	8.07	(18.09)	9.36	(28.03)
Observations	1,099		3,919		834	

Notes: This table reports descriptive statistics at the supplier level. The treated group consists of suppliers to special taxpayers selected in February 2018, whose sales to these firms represented at least 40% of their total sales during the second semester of 2017. The control groups include: (i) suppliers to special taxpayers selected in 2021, and (ii) large non–special taxpayer firms with comparable levels of client dependency. Panel A reports statistics for all suppliers. Panel B focuses on suppliers that are individually owned firms, while Panel C reports statistics for corporate suppliers. The total number of suppliers in Panel A slightly exceeds the sum of Panels B and C because it also includes taxpayers classified under the *Economía Popular y Solidaria* (e.g., associations). Return to the main text.

Sample selection to study the reform of 2015. The reform of 2015 targeted special taxpayers by introducing withholding in the transactions between them. In principle, one could compare special taxpayers to other large firms that were not subject to the reform and whose method of VAT remittance remained unchanged. However, these potential control firms were already subject to withholding mechanisms. As a result, this comparison would imply the use of already-treated firms as controls for newly treated ones.

To address this challenge, I exploit variation in treatment intensity along the intensive margin. I measure exposure as described above and, following Garrett et al. (2020), Curtis et al. (2021), Pineda et al. (2024), and Koizumi (2024), construct a binary treatment indicator based on the exposure variable. Specifically, I define treated firms as those with an exposure above the 75th percentile and control firms as those below the 25th percentile. After implementing these restrictions, I have 877 firms in the treatment group and 870 firms in the control group.[21] Panel A of Table 2.2 presents descriptive statistics on the distribution of the exposure measure.

As discussed in Section 2.2.1, withholding rates were initially set at 30% for goods and 70% for services during the first quarter of 2015. Withholding was temporarily suspended in April and May (the second quarter of 2015), and from June 2015 onward, withholding rates were lowered to 10% for goods and 20% for services. Considering these policy changes, I aggregate the VAT data at the quarterly level for the empirical analysis. Table 2.2 presents descriptive statistics for the treatment and control groups in the last quarter of 2014, just before the implementation of withholding.

21. I exclude firms in the construction sector that are always subject to withholding.

Table 2.2. Descriptive Statistics. Reform of 2015

	Panel A. Exposure = taxable trade with special taxpayers/taxable sales			
	percentile 25	percentile 50	percentile 75	mean
Exposure	3.03	17.34	55.34	31.15

	Panel B. Summary statistics Variables expressed in 2018 USD (thousands)			
	Treated group		Control Group	
	High exposure		*Low exposure*	
	Mean	SD	SD	
Taxable Sales (USD thousands)	3814.88	(7693.00)	1981.20	(5745.75)
Taxable Purchase	3235.91	(6279.91)	1661.72	(4367.31)
Output Vat	457.79	(923.16)	237.74	(689.49)
Input VAT	388.31	(753.59)	199.41	(524.08)
VAT due	144.93	(302.51)	73.66	(246.48)
Withholding	0.69	(4.17)	0.97	(4.40)
Tax Liability	193.01	(362.86)	88.68	(274.22)
Tax Credit due to Withholding	6.30	(36.06)	4.08	(26.12)
Tax credit at the end of the quarter	318.44	(929.98)	133.20	(569.39)
Unclaimed Tax Credit	484.72	(1442.75)	201.22	(886.44)
VAT Remittance	569.91	(1794.83)	240.61	(1349.18)
Prob (tax credit due to whitholding >0)	0.06	(0.24)	0.13	(0.33)
Prob (unrefunded balance >0)	0.48	(0.50)	0.58	(0.49)
Prob (total credit >0)	0.43	(0.50)	0.54	(0.50)
Observations	878		870	

Notes: This table reports descriptive statistics at the firm level. Treated firms are special taxpayers with pre-reform exposure above the 75th percentile. Control firms are also special taxpayers that had a pre-reform exposure below the 25th percentile. All variables are transformed to real values using the 2018 consumer price index and are winsorized at the 99th percentile.Return to the main text.

2.4 Theoretical background

Based on existing literature, I formulate hypotheses to explain how the selection of special taxpayers influences the behavior of their suppliers. The special taxpayer program is designed to increase tax revenue by increasing tax monitoring and enforcing VAT remittance through withholding. Understanding the mechanisms through which this program affects suppliers requires considering that not all suppliers are affected in the same way. Some are only affected through an increase in the perceived audit risk, while others are affected by both changes in the remittance process and an increase in the perception of monitoring.

The potential mechanisms that affect suppliers are summarized in the following hypotheses:

Withholding and Enforcement-Perception Mechanism. Under this mechanism, withholding signals to the supplier that the tax authority is paying closer attention to transactions to which it applies (Brockmeyer and Hernandez, 2022). Even when third-party reporting systems are in place, suppliers might perceive that transactions affected by withholding are subject to more inspection by the tax authority.

Hypothesis 1. If a supplier previously under-reported transactions with special taxpayers but now reports them accurately due to the withholding mechanism, we should observe an increase in reported sales, and correspondingly, in output VAT and VAT due.

Withholding as a Default Payment Mechanism. This mechanism captures the effect of withholding on the accumulation of VAT credits. Withholding may increase the likelihood that suppliers accumulate excess VAT credits, as they receive credits for both input VAT and VAT withheld by their clients (Keen and Smith, 2007). If firms face frictions or costs when claiming these refunds, some may opt not to request reimbursement, and this effectively makes the withheld amount their final tax payment (Brockmeyer and Hernandez, 2022). Even when refunds are eventually claimed or carried forward to future periods, delays in administrative procedures can lead to temporary increases in tax revenue.

Hypothesis 2. Suppliers of special taxpayers are more likely to accumulate VAT credits due to their exposure to withholding.

Positive Spillovers of Monitoring. Studies of enforcement spillovers in local networks find that monitoring can improve reporting behavior among non-targeted taxpayers who are connected to those under inspection (e.g., Lediga et al., 2023; Rincke and Traxler, 2011).

Hypothesis 3. Suppliers of special taxpayers improve their reporting behavior due to their clients being subject to stricter monitoring, leading to an increase in VAT due.

Disruption of Informal Cost-Inflation Practices. Firms designated as special taxpayers may adjust their reporting behavior in response to increased monitoring, particularly with respect to costs and sales. These adjustments can indirectly affect their suppliers, especially in the presence of informal agreements aimed at inflating clients' deductible costs prior to selection.

The asymmetric incentives of the VAT system generally discourage suppliers from engaging in cost inflation (Pomeranz, 2015), since reporting higher sales increases their output VAT liability. However, these practices may still occur when clients have market power. In those cases, suppliers who are highly dependent on large clients may be more willing to participate in these informal arrangements in order to preserve business relations.

Once the clients are selected as special taxpayers, the increased monitoring may deter these practices. As a result, one may observe a decline in the supplier's reported sales and output VAT.

Hypothesis 4. Following the selection of clients as special taxpayers, their suppliers reduce their reported sales and consequently, their output VAT, reflecting a disruption of informal cost-inflation practices.

2.5 Research Design

2.5.1 Studying the effects of the selection of special taxpayers on their suppliers

To estimate the effect of the 2018 selection of special taxpayers on suppliers, I use firm-to-firm network data in the second semester of 2017 (*pre-treatment semester*) to construct a measure of each supplier's exposure to selected clients.

$$\text{Exposure}_i = \frac{\text{Sales to Special Taxpayers selected in } 2018_i}{\text{Total Taxable Sales}_i}, \tag{2.1}$$

The ratio captures the intensity of trade with clients that will become special taxpayers. To create a comparable control group, I calculate an analogous measure for sales to large firms that were not designated as special taxpayers.

For the empirical analysis, I transform the continuous exposure measure into a binary treatment indicator. A supplier is assigned to the treated group if at least 40% of its taxable sales were to firms later designated as special taxpayers. The control group includes suppliers for whom at least 40% of taxable sales were to large firms that were not designated. I exclude suppliers with high exposure to special taxpayers selected before 2018 (defined as at least 40% of total sales) from the control group.

To construct the exposure measure, I use sales to large clients as reported by the clients in the purchases annex and the taxable sales as reported by the supplier in the VAT returns. A potential concern is that suppliers may under-report their taxable sales to reduce their VAT liability. However, such behavior is likely to affect both treatment and control groups similarly, especially in a context of widespread or systematic evasion. I do not have any evidence to believe that this issue differs between suppliers of selected and non-selected special taxpayers in the semester before selection. Further, I do not use the continuous exposure measure directly in the empirical analysis. Instead, I use a binary treatment indicator, which helps mitigate concerns about measurement error.

As mentioned in Section 2.3.2, I use two control groups. Control group 1 is used in the main specifications. To explore the heterogeneity of the results, I also use alternative exposure thresholds of 30% and 20%.

Next, I implement a differences in differences strategy to estimate the effect of the selection of clients on supplier outcomes. The baseline specification is shown in Equation 2.2:

$$y_{it} = \theta \cdot \text{Post}_t \times \text{Treated}_i + \lambda_t + \omega_i + \varepsilon_{it}, \tag{2.2}$$

In this specification, y_{it} is the outcome of interest for supplier i in period t, such as output VAT, VAT due, or VAT credits. The variable Treated_i is an indicator equal to one if supplier i was highly exposed to clients that are selected as special taxpayers in 2018. Post_t is a dummy equal to one for post-treatment periods. The term ω_i captures supplier fixed effects, and λ_t denotes time fixed effects. I apply a hyperbolic sine transformation to outcome variables to handle the presence of zeroes.

The coefficient of interest is θ, which captures the average effect of clients' designation as special taxpayers on the supplier's outcomes. A positive θ when the outcome is output VAT or VAT due would be consistent with Hypothesis 1 (enforcement-perception mechanism), or Hypothesis 3 (*positive spillovers of monitoring*). A negative coefficient, by contrast, would support Hypothesis 4, which establishes a disruption of cost-inflation practices.

The dynamic treatment effects are estimated as follows:

$$y_{it} = \sum_{k \neq -1} \theta_k \cdot \mathbb{1}(t = k) \cdot \text{Treated}_i + \lambda_t + \omega_i + \varepsilon_{it}, \tag{2.3}$$

where θ_k is a set of time indicators for k periods relative to the treatment, excluding the reference period $k = -1$ (second semester of 2017). The coefficients θ_k capture the dynamic effects of exposure to a client that is designated as a special taxpayer. All specifications include supplier and time fixed effects. I focus on semesters in the range $k \in [-4, 4]$, covering four semesters before and after the selection of a client as a special taxpayer. Standard errors are clustered at the supplier level.

2.5.2 Empirical strategy to study the reform of 2015.

To estimate the effect of the 2015 reform that introduced VAT withholding between special taxpayers, I implement a difference-in-differences strategy that exploits variation in firms' exposure to the policy along the intensive margin. I compute exposure in 2014 as the ratio between sales to special taxpayers to total sales. I define treated firms as those with pre-reform exposure above the 75th percentile and control firms as those below the 25th percentile. The empirical analysis is conducted at the firm-quarter level.

The baseline specification is shown in Equation 2.4

$$y_{it} = \beta \cdot \text{Post}_t \times \text{High Exposure}_i + \alpha_i + \gamma_t + \upsilon_{it}, \tag{2.4}$$

where y_{it} is the outcome of interest (e.g., VAT remittance, VAT due, VAT credits) for firm i in quarter t. The variable High Exposure$_i$ is an indicator equal to one for firms with exposure above the 75th percentile in 2014. Post$_t$ is a dummy for quarters after the reform was implemented (beginning in the first quarter of 2015). α_i and γ_t capture firm and time fixed effects, respectively. I apply a hyperbolic sine transformation to outcome variables to handle the presence of zeroes.

The coefficient of interest is β, which captures the average effect of the reform on treated firms relative to the control group. A positive value of β when the outcome is VAT due would be consistent with Hypothesis 1, as it would suggest that the introduction of withholding improved compliance. If β is not statistically significant for VAT due, but is positive and significant when the outcome is VAT credits, this would support Hypothesis 2. This hypothesis proposes that withholding affects VAT remittances by increasing the accumulation of VAT credits, even in the absence of a compliance effect.

To examine the dynamic effects of the reform over time, I also estimate an event-study specification. This allows me to test for the presence of differential pre-trends between treated and control firms and to explore how the effects of the reform evolve across quarters following implementation.

$$y_{it} = \sum_{q \neq -1} \beta_q \cdot \mathbb{1}\{\text{High Exposure}_i\} \cdot \mathbb{1}\{\text{Quarter} = q\} + \alpha_i + \gamma_t + \upsilon_{it}, \tag{2.5}$$

I focus on quarters in the range $q \in [-8, 8]$, covering eight quarters before and after the reform. Throughout the analysis, standard errors are clustered at the firm level.

2.5.3 Can suppliers anticipate the selection of special taxpayers?

Before analyzing the empirical results, it is important to discuss whether suppliers can anticipate the inclusion of their clients in the special taxpayers program. As discussed in Section 2.2.2, the specific inputs used to construct the eligibility score, as well as the weights assigned to them, are not publicly disclosed and may change from year to year. The restricted access to this information makes it highly unlikely that firms or their suppliers can accurately anticipate their selection. First, firms are unlikely to know the precise inputs or their importance in the scoring algorithm. Second, because the score is based on a firm's percentile ranking within its province, anticipating selection would require detailed knowledge of other firms' reported tax returns, an implausible assumption given the confidentiality of tax data. Third, the Tax Agency applies province-specific thresholds for the selection (De Simone, 2022), adding another layer of complexity and unpredictability, which complicates any attempt at prediction. Finally, even if a firm suspected it was close to the cutoff, strategically adjusting its score would require retroactive amendments to previously filed tax returns, since the selection is based on past information. This is a costly procedure.

To assess whether firms engage in strategic reporting to change their provincial rankings, I examine possible signs of manipulation in the inputs used during one of the earliest selection rounds, as detailed in Section 2.2.2. If firms want to avoid the selection, they may attempt to manipulate these inputs. I specifically examine whether there is any visible bunching in the distribution of the rankings used to construct the score, particularly near the upper end. Figure 2.C.4 presents histograms of these rankings. The distributions of the outcomes are smooth, with no excess mass or clustering at the top. This suggests that firms do not manipulate their rankings to influence the selection process.

Given the uncertainty surrounding the selection criteria, the complexity of the score's construction, and the absence of evidence of bunching, it is unlikely that suppliers could anticipate their clients' inclusion in the program. This supports the validity of the identification strategy used to analyze the indirect effects of the selection in Section 2.6.1. Further, the absence of pre-trends in the dynamic difference-in-difference specifications would provide additional support for this assumption.

2.6 Results

2.6.1 Effects of the selection of special taxpayers on their suppliers

This section presents the indirect effects of the 2018 client's selection as special taxpayers on suppliers. The effects are estimated using treated suppliers whose exposure to designated clients exceeds 40 percent of their taxable sales. Suppliers of large but non-designated firms are the control group. Since the selection of special taxpayers took place in February 2018, suppliers remained untreated for the first two months of the first semester of 2018. This is marked in purple in the figures of this section.

As a first stage of the policy, I examine the consequences of being selected as a special taxpayer on withholding reported by their suppliers. When a firm is selected as a special taxpayer, it becomes responsible for collecting the VAT on transactions with corporate firms. As shown in Panel a of Figure 2.1, these corporate suppliers experience an increase in the amount of VAT withheld by their clients. Further, there is a significant increase in the probability that suppliers report a withholding-related tax credit.

Corporate suppliers of special taxpayers experience an increase of approximately 16 percentage points in the likelihood of reporting a tax credit. Given a baseline reporting rate of 47%, this corresponds to a relative increase of about 34%. Therefore, the probability of reporting a credit increases to 63% on average. This increase in reported credits could have an effect on firm liquidity, as VAT credits are typically refunded with a delay or carried forward against future liabilities. This finding provides initial evidence in support of Hypothesis 2, which proposes that the withholding mechanism influences the remittance process by increasing the accumulation of VAT credits among affected suppliers. Table 2.B.3 reports the corresponding regression estimates.

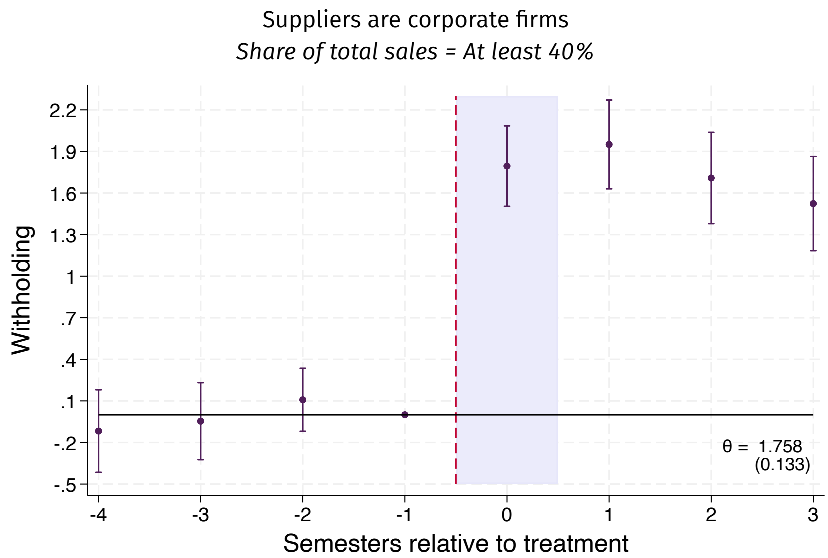
Next, I present the main results on the effects of clients' designation as special taxpayers. As discussed in Section 2.2.2, the impact on suppliers varies by legal form. Individually owned firms are affected only through the spillover effects from the intensified monitoring of their selected clients. In contrast, corporate suppliers are exposed to both the increased monitoring and the introduction of VAT withholding on transactions with the selected clients. Accordingly, I present and discuss the results separately for each group.

Effects on individually owned firms

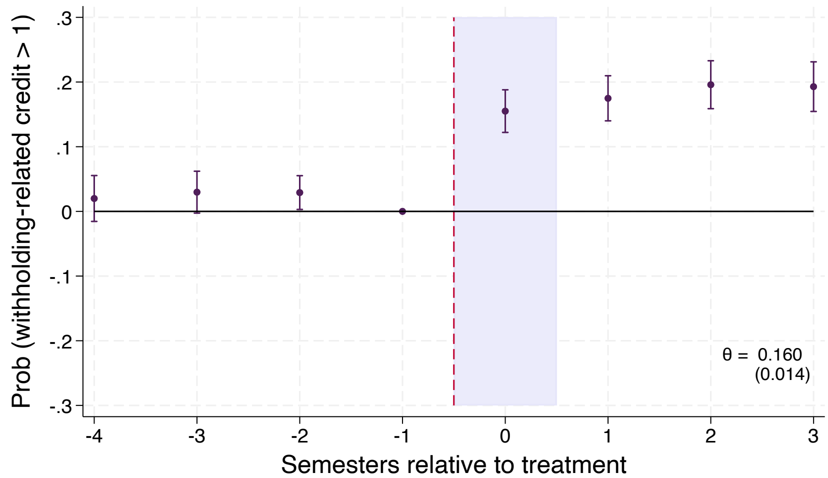
The relevant hypotheses to be tested for this group are Hypotheses 3 and 4. A positive effect on VAT due would support Hypothesis 3 and would suggest that increased monitoring of the client improves the reporting behavior of the supplier through enforcement spillovers. In contrast, a negative effect on VAT due would be in line with Hypothesis 4, indicating a potential disruption of cost-inflation practices between the client and the supplier.

Figure 2.2 presents the estimated effects of clients' selection on the supplier's reported output VAT and VAT due. The absence of pre-trends provides evidence that treated and control suppliers were comparable prior to treatment and did not anticipate the clients' designation. The results show statistically significant reductions of approximately 16.4% in output VAT and 15.9% in VAT due. Based on a baseline

Figure 2.1. First stage of selection of a client as special taxpayer



(a) First stage: withholding



(b) Tax credit

Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.2. Treatment and control groups include corporate firms. The control group used in the figures is the suppliers of large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

output VAT of USD 2,558, this corresponds to a decline of USD 420 per semester. Similarly, VAT due falls by about USD 279 from a baseline of USD 1,753.

These findings provide evidence in support of Hypothesis 4. The decline in output VAT and VAT due suggests that, following the client's designation, arrangements aimed at inflating costs were disrupted. This interpretation is reinforced by the asymmetric relation between the large clients and the suppliers: high dependency on these large clients increases the likelihood that suppliers engage in such practices to benefit the client.

To examine the role of suppliers' exposure, I estimate the effects using alternative thresholds. Figure 2.A.1 presents results for suppliers with at least 30 percent of their sales linked to the large clients, and Figure 2.A.2 reports the effects for a 20 percent threshold. As the exposure threshold decreases from 40 to 30 and 20%, the estimated effects on VAT due attenuate but remain statistically significant. Specifically, the reduction in VAT due is 13.1% for the 30% exposure group and 10.3% for the 20% exposure group. This finding is consistent with the interpretation that a stronger dependency on large clients increases the likelihood of cost-inflation arrangements. Further, the attenuation of the effect is also consistent with what one would expect if adjustments are concentrated on transactions with the special taxpayers rather than on all suppliers' sales. Table 2.B.4 presents the corresponding results.

As a robustness check, Figure 2.A.3 presents the results using suppliers linked to firms designated as special taxpayers in 2021 as the control group. The findings remain consistent: I observe statistically significant reductions in both output VAT and VAT due, providing further support to Hypothesis 4. The estimated effects are somewhat larger in this specification and of approximately 24.4% for output VAT and 22.8% for VAT due. Table 2.B.5 presents the corresponding results.

As a second robustness check, I exclude from the treated group those suppliers with high exposure to clients designated as special taxpayers prior to 2018 (defined as at least 40% of total sales), in line with the restriction already imposed on the control group. As explained before, the treated suppliers are excluded from the sample used to construct the control groups. Thus, suppliers in the control group do not have more than 40% of their sales with the new special taxpayers. However, they can have small shares of trade. To verify that this does not affect my results, I further restrict the control group by excluding firms that reported any trade with the new special taxpayers. Figure 2.A.4 shows that the results are very similar to those of the main specification: output VAT decreases by 16.1% and VAT due by 15.2%.

The selection of special taxpayers is published on the Tax Agency's website and reported by newspapers (De Simone, 2022), thus, taxpayers can check each other's status.[22]. However, some taxpayers may not pay attention to this information. This can be problematic if some special taxpayers hide their status to avoid changes in the behavior of their suppliers. In this case, the results will underestimate the true effect.

Effects on corporate firms

Corporate firms are affected by the clients' selection through a combination of monitoring and withholding. Figure 2.3 presents the results for output VAT and VAT due. However, the pre-trends of these variables are not as clean as in the analysis of individually owned firms. Therefore, the evidence on mechanisms for this group is suggestive rather than conclusive. There seems to be a reduction in output VAT following the clients' selection, despite pre-trends moving in the opposite direction. VAT due also declines, although this change is not statistically significantly different from zero.

Under Hypothesis 1, the expected effect of withholding is an increase in both output VAT and VAT due. The observed reductions, although suggestive, instead give some support to Hypothesis 4, which proposes a different behavioral response to the policy. Further, as previously noted, Panel B of Figure 2.1 suggests an increase in the probability of reporting a withholding-related tax credit, which again suggests that, if any, withholding operates as a default-payment mechanism (Hypothesis 2).

2.6.2 Extending withholding to presumed compliant taxpayers: effects of the 2015 reform

In this Section, I examine the effects of implementing VAT withholding on transactions between special taxpayers. As discussed in Section 2.4, withholding can influence firms' VAT declarations through two channels. The first is the *enforcement-perception* channel (*Hypothesis 1*), under which firms report more accurately when they believe the tax authority is monitoring their transactions more closely (Brockmeyer and Hernandez, 2022). The second is the *default payment* channel (*Hypothesis 2*), which leads firms to accumulate VAT credits when claiming a refund is perceived as costly (Keen and Smith, 2007).

To estimate the effects of the reform, I exploit variation in firms' exposure to trade with other special taxpayers. Firms in the treatment group are those with pre-reform exposure above the 75th percentile, while those in the control group

22. For example, the newspaper *Diario La Hora* published an article announcing the latest selection of special taxpayers in June 2025. It can be read here: https://www.lahora.com.ec/economia/SRI-actualiza-lista-de-contribuyentes-especiales-Como-saber-si-esta-en-esa-lista-y-las-nuevas-obligaciones-tributarias-desde-junio-2025-20250605-0010.html. The current list of special taxpayers can be found here: https://www.sri.gob.ec/catastros

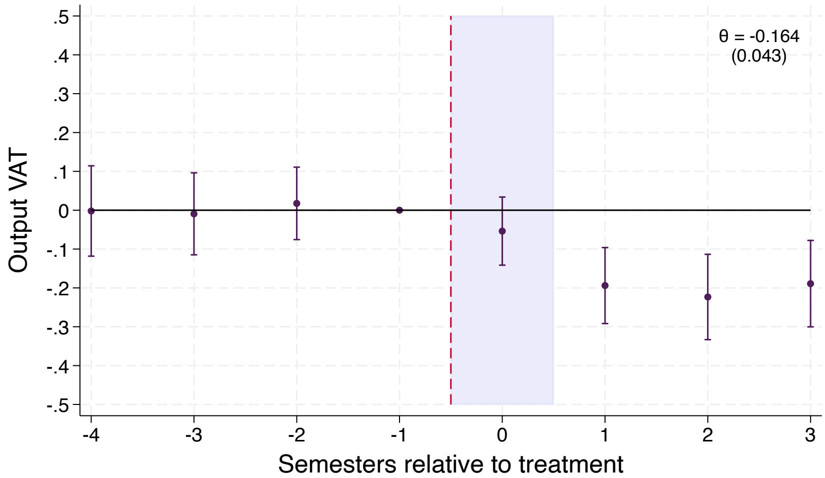
have exposure below the 25th percentile. I begin by presenting the first-stage of the reform in Figure 2.4, which shows how treated firms experienced an increase in VAT withheld starting in 2015. On average, more exposed firms experienced an increase of USD 59,130 in the amount of VAT withheld from them, relative to less exposed firms.

There are three key patterns to analyze from the first-stage figure. First, before the reform, special taxpayers could have been subject to withholding when supplying goods or services to government entities or the public sector. Despite this, both treated and control firms present similar levels of withholding prior to the reform, suggesting comparable pre-trends. Second, there is a sharp increase in withholding in quarter 0 (first quarter of 2015), which reflects the unusually high withholding rates applied during this period (e.g., 70% for services and 30% for goods.) To better illustrate the evolution of withholding in subsequent periods, Panel b excludes this outlier quarter. Third, withholding was suspended in April and May of 2015 to revise the applicable rates (e.g., 20% for services and 10% for goods). This revision period helps explain why the difference in withholding between treated and control firms narrows temporarily in quarter 1.

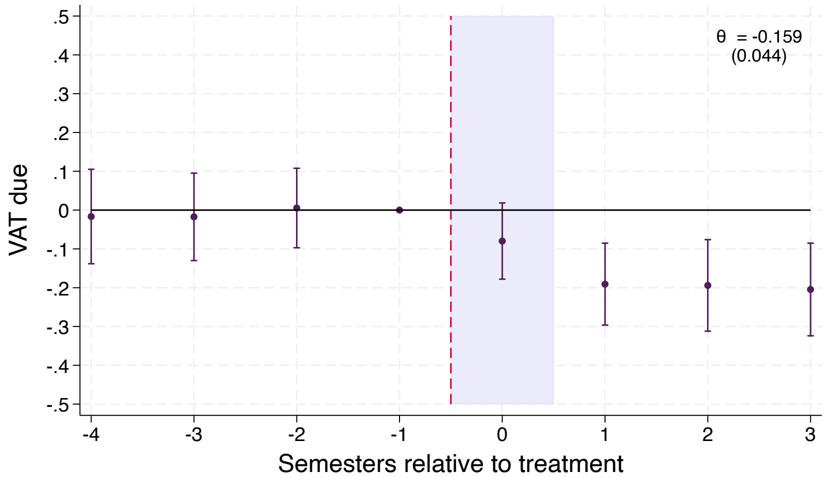
To capture the firm's overall tax remittance behavior, I construct a variable called VAT remittance, defined as the VAT liability if it is positive, or the reported VAT credit if the liability is zero. This variable reflects the total amount of VAT declared by the firm as due to the tax authority, either paid directly or indirectly through amounts withheld by clients. Table 2.3 presents differences in differences estimates obtained using Equation 2.4. Treated firms increased their VAT remittance by approximately 23.5% after the introduction of the reform. This result is corroborated by the dynamic estimates shown in Panel a of Figure 2.5.

Figure 2.2. Spillover effects of monitoring large taxpayers on individually owned firms

Share of total sales = At least 40%



(a) Output VAT



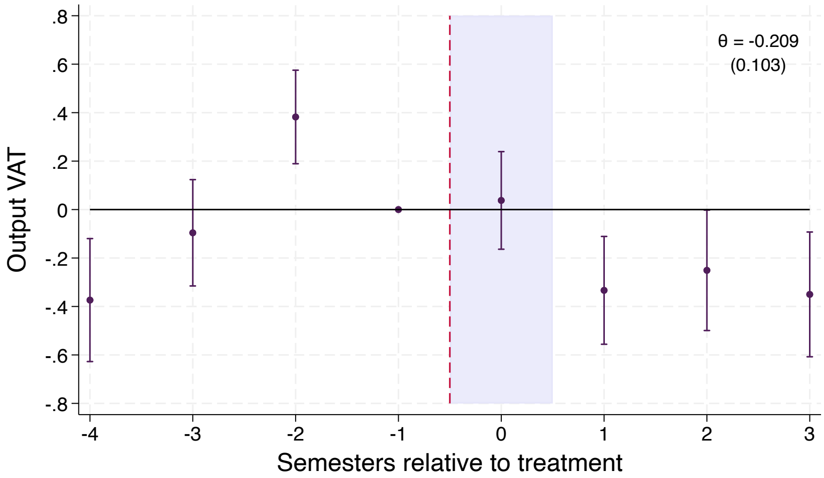
(b) VAT due

Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures is the suppliers of large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

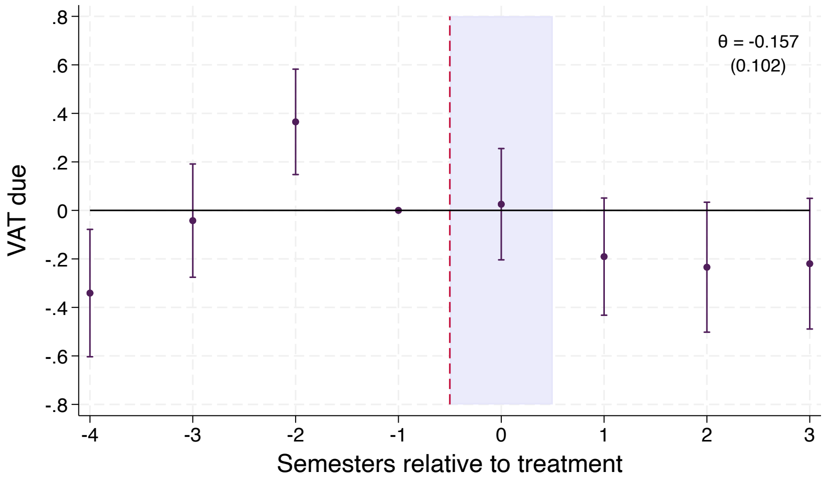
Figure 2.3. Spillover effects of monitoring large taxpayers on corporate firms

Control group: Suppliers of large firms

Share of total sales = At least 40%



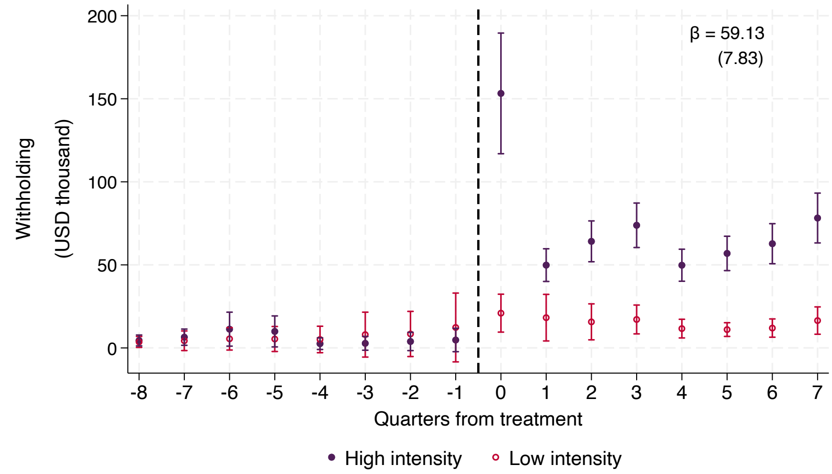
(a) Output VAT



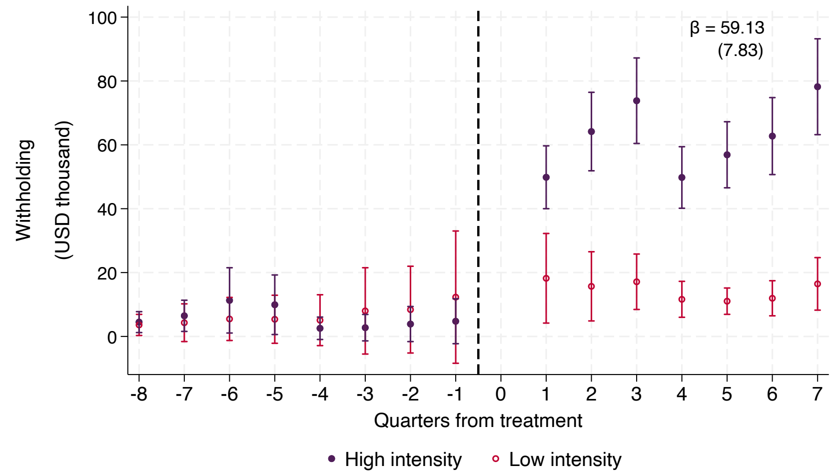
(b) VAT due

Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures is the suppliers of large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.4. First Stage: Introduction of Withholding in Transactions Between Special Taxpayers



(a) Withholding (all quarters included)



(b) Withholding (first quarter excluded)

Notes: These figures illustrate the increase in withholding for the treated group (*high-exposure firms*) following the introduction of withholding between special taxpayers. High-exposure firms are defined as those with exposure above the 75th percentile, while control firms fall below the 25th percentile. Exposure is measured as the ratio of sales to special taxpayers to total sales. Quarter 0 refers to the first quarter of 2015. The first figure includes all the quarters. However, since withholding rates were unusually high in the first quarter after the reform (i.e., 70% for services and 30% for goods), the second figure excludes this quarter to better show the increases in withholding in subsequent periods. Note that withholding was suspended in April and March 2015 to allow for the implementation of the modified withholding rates. Return to the main text.

This increase in the VAT remittance may result from a compliance response, consistent with the *enforcement perception* channel (*Hypothesis 1*), or from an increase in VAT withheld by clients, which increases reported credits and may lead to higher unclaimed tax credits (*default payment* channel, *Hypothesis 2*). To investigate whether the increase reflects improved compliance, I examine the effect on VAT due, shown in Column 2 of Table 2.3). The estimated effect is not statistically significant from zero. However, a temporary increase is observed in the first treated quarter, which coincides with the period when unusually high withholding rates were applied (Panel b in Figure 2.5). This finding suggests that the *enforcement perception* channel is not the main mechanism in this setting. Special taxpayers are already subject to monitoring by the tax authority, which means withholding does not have an effect on compliance behavior.

I next explore whether the increase in VAT remittance can be explained by the *default payment* channel. To do so, I focus on extensive margin responses, specifically the likelihood of reporting a withholding-related tax credit associated or an unclaimed tax credit. Panel a of Figure 2.6 shows that, following the reform, there was an increase in the probability that firms reported a withholding-related tax credit. As shown in Column 3 of Table 2.3, more exposed firms were 21.4 percentage points more likely to report a tax credit. Given a baseline reporting rate of 12.5%, the effect corresponds to a relative increase of about 171% on average. These credits are carried forward to offset future VAT liabilities since exposed firms report unclaimed tax credits. Column 4 of Table 2.3 shows that the probability of reporting an unclaimed tax credit increased by 14.2 percentage points for more exposed firms. Given a baseline reporting rate of 57.8%, this corresponds to a relative increase of about 25% on average. The dynamic effects are reported in Panel b of Figure 2.6. These results suggest that the increase in VAT remittance reflects persistent excess credits that remain unclaimed, increasing tax revenue at the expense of the firms' liquidity. This increase in the probability of reporting credits is important because it implies a shift of liquidity from firms to the government.

Table 2.3. Effects of the reform of 2015

	VAT remittance (1)	VAT due (2)	Probability of withholding related credit (3)	Probability of reporting unclaimed tax credit (4)
High exposure x Post	0.235***	0.087	0.214***	0.142***
	(0.094)	(0.106)	(0.018)	(0.014)
Mean Dep Variable in q=-1 (USD thousands)*	241	87	0.125	0.578
Observations	27,641	27,641	27,641	27,641

Notes: This table presents the effects of the implementation of withholding between special taxpayers in 2015. Estimates are from a differences in differences specification following Equation 2.4. All outcome variables are transformed using the hyperbolic sine function, after adjusting all monetary values to 2018 prices. The specifications include firm and time fixed effects. The mean dependent variable corresponds to the control group in the last quarter of 2014 (q = -1). Standard errors are clustered at the firm level.
* Mean dependent variable is the corresponding probability of the treatment group in Column 3.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Return to the main text.

As robustness checks, Tables 2.B.7 and 2.B.8 present results using alternative definitions of treatment and control groups. In Table 2.B.7, firms with exposure above the 70th percentile are treated, and those below the 30th percentile are part of the control group. In Table 2.B.8, the thresholds are tightened: treated firms have exposure above the 80th percentile, and control firms fall below the 20th percentile. Figures 2.A.5 and 2.A.6 show the corresponding dynamic treatment effects.

Effect on VAT revenue. I use a back of the envelope calculation to approximate how unclaimed tax credits translate into VAT revenue. I begin by estimating Equation 2.4 using the unclaimed tax credits, conditional on being positive, as the outcome variable. More exposed firms increased their unclaime credits by 70.7% following the reform (Figure 2.A.7).[23] To express this semi-elasticity in monetary terms, I multiply it by the pre-reform mean unclaimed tax credits among control firms (USD 201,000), resulting in an estimated increase of approximately USD 142,000. Because the unclaimed credit is a *stock* variable, this increase represents the additional cash the tax agency holds at any given time, rather than an amount that accumulates throughout the year.

Next, I compute the expected increase in the unclaimed tax credit per treated firm, accounting for both the higher probability of reporting a tax credit and the

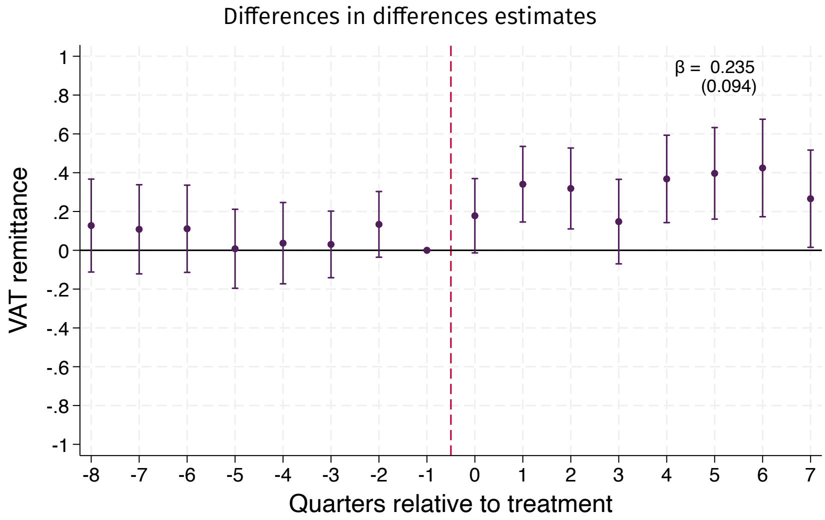
23. Computed as $\exp(0.5353537) - 1 = 1.706869 - 1 = 0.706869 = 70.7\%$.

increase in the average tax credit amount. Prior to the reform, 57.8% of firms reported a positive unclaimed tax credit. After the reform, more exposed firms were 14.2 percentage points more likely to report a credit. Considering both the intensive and extensive margins, the expected additional unclaimed tax credit per treated firm is:

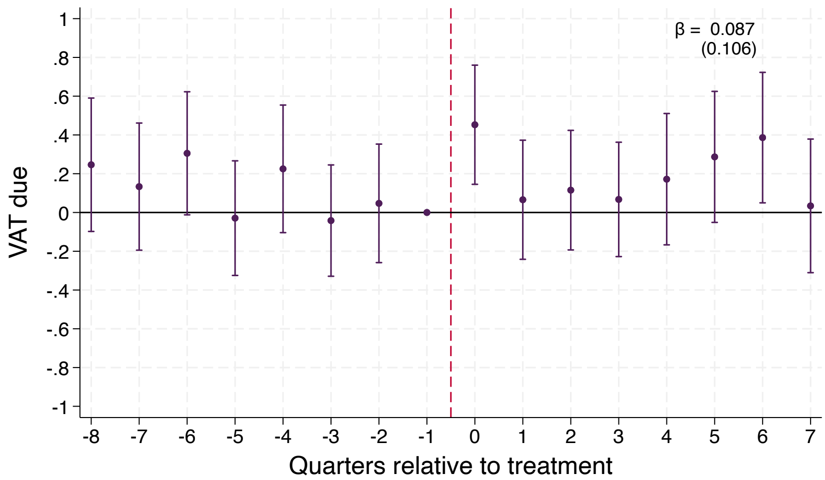
$$\Delta E[credit] = (p_0 + \Delta p)(credit_0 + \Delta credit) - p_0 credit_0 \approx 131{,}000 \text{ USD} \tag{2.6}$$

Where p_0 represents the control group's mean probability of reporting and unclaimed credit, and $credit_0$ is the control group's mean unclaimed tax credit. Assuming that the 878 treated firms experienced this increase, the tax authority holds approximately USD 115 million in additional unclaimed tax credits, which represents about 2.4% of the total VAT revenue collected in 2015. However, these amounts are temporary cash flow gains for the government, since firms can still use the credits to offset future liabilities, or a refund can be requested.

Figure 2.5. Effects of the 2015 reform on VAT remittance and VAT due



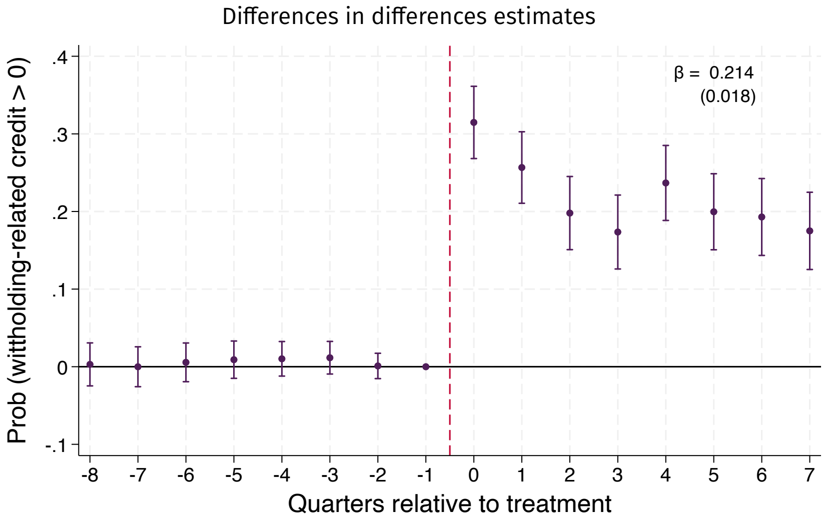
(a) VAT remittance



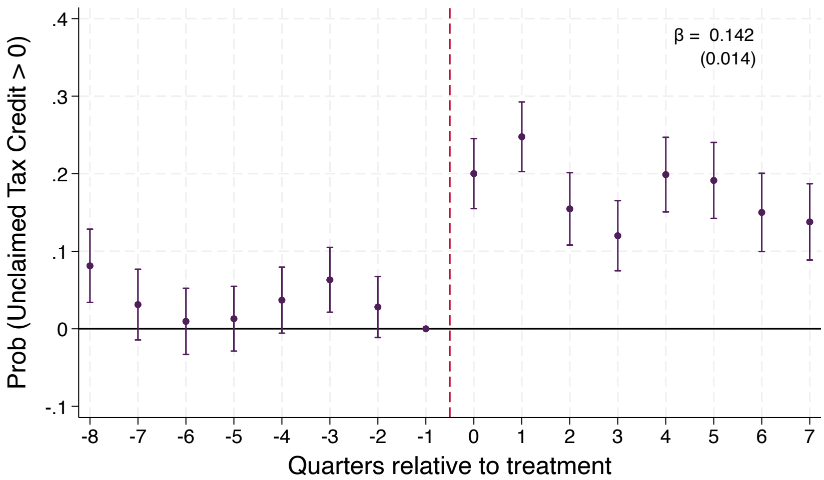
(b) VAT due

Notes: This plot shows the dynamic effects of the introduction of withholding between large taxpayers in 2015. The effects were estimated using Equation 2.5, and I exploit variation from the intensive margin of the reform. The empirical analysis uses quarterly panel data and includes firm and time fixed effects. The estimation window covers 8 quarters before and after treatment. The dependent variables are transformed using the hyperbolic sine function, after adjusting all monetary values to 2018 prices. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.6. Effects of the reform of 2015 on tax credit and unrefunded balance



(a) Probability of reporting a withholding-related tax credit



(b) Probability of reporting an unclaimed tax credit

Notes: These plots show the dynamic effects of the introduction of withholding between large taxpayers in 2015. The effects were estimated using Equation 2.4, and I exploit variation from the intensive margin of the reform. The empirical analysis uses quarterly panel data and includes firm fixed effects and time fixed effects. The time window covers 8 quarters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

2.7 Discussion and Conclusions

The tax monitoring strategy of the Ecuadorian government focuses on large taxpayers and uses their supply chains to expand enforcement coverage. These large firms transmit enforcement shocks to their suppliers through monitoring and withholding of taxes. This paper studied how suppliers respond to these enforcement shocks. The empirical evidence shows that suppliers reduce their output VAT and VAT due after the selection of large clients as special taxpayers. For corporate suppliers, this decrease is observed even though VAT withholding is introduced simultaneously with the selection of the clients, and is expected to have the opposite effect.

These results support the hypothesis of disruption of cost-inflation practices between large firms and their suppliers. If large clients were previously over-reporting their costs to reduce their VAT liabilities, their inclusion in the program prevents this behavior. The findings suggest that the over-reporting of costs is not done unilaterally but involves coordination with suppliers. This coordination may be possible due to the asymmetric relation between large clients and smaller suppliers.

De Simone (2022) estimates that firms selected into the special taxpayers program increase their corporate income tax payments by an average of USD 8,000 and reduce revenue discrepancies between their tax returns and third-party reporting sources. By studying the indirect effect of the policy, I provide evidence that over-reporting of costs is also part of the evasion strategy of these firms through transactions with suppliers. I estimate an average reduction in the VAT due of USD 279 per supplier and semester, which translates into an annual reduction of USD 558 per supplier. These reductions do not imply a negative effect of the program since the special taxpayers increase their corporate income tax payments. Although the effects on suppliers are modest in size, they inform the government about the evasion strategy of the large firms.

The results of the second policy variation studied in this paper are used to asses the effects of withholding in transactions where clients and suppliers are special taxpayers. When monitoring is in place on the two parties of the transaction, withholding does not have an effect on VAT due. The absence of effect indicates that withholding does not work as a compliance tool in this setting. However, I find an effect on unclaimed tax credits. Using a back-of-the-envelope calculation, I estimate that unclaimed tax credits increase by USD 131,000 per treated firm. This amount reflects a temporary gain in tax revenues for the government since some liquidity is shifted from the firm to the government. Future research could study whether the introduction of withholding between special taxpayers has effects on the liquidity and performance of the firm to evaluate the costs of the policy.

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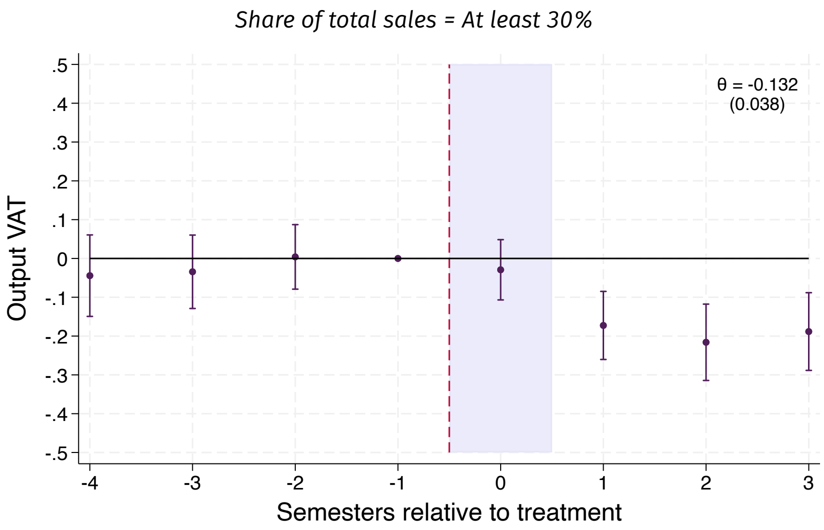
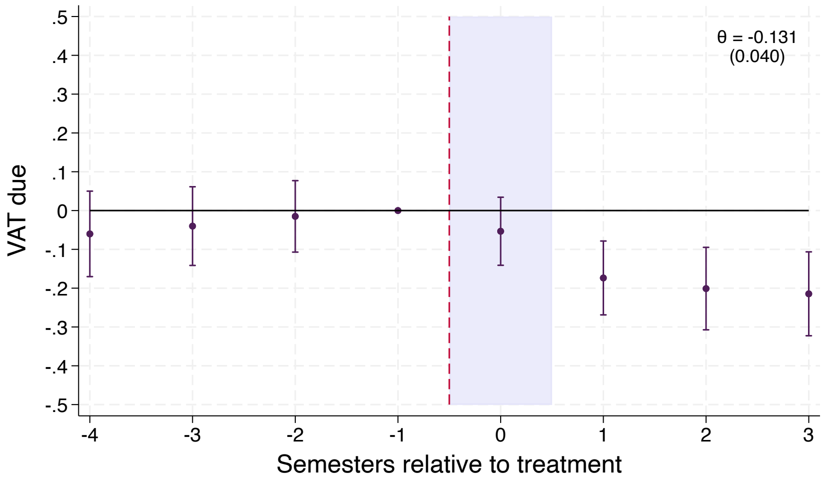
2.A Additional Figures

Figure 2.A.1. Spillover effects on individually owned firms. 30% Threshold



(a) Output VAT

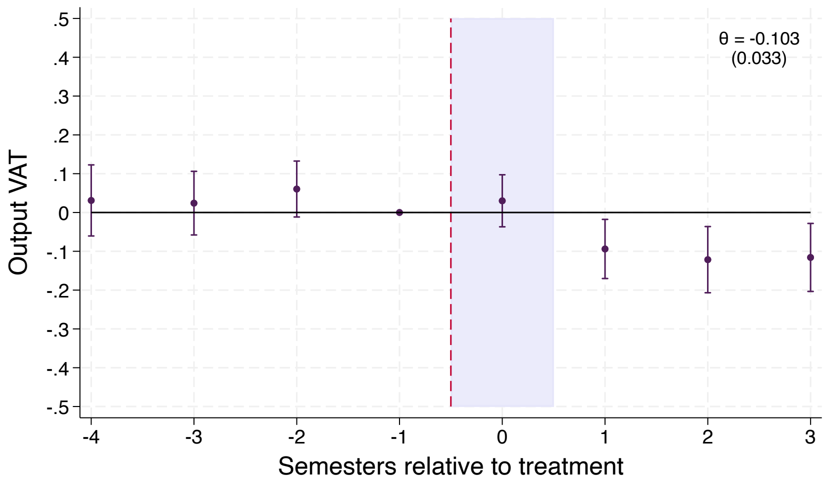


(b) VAT due

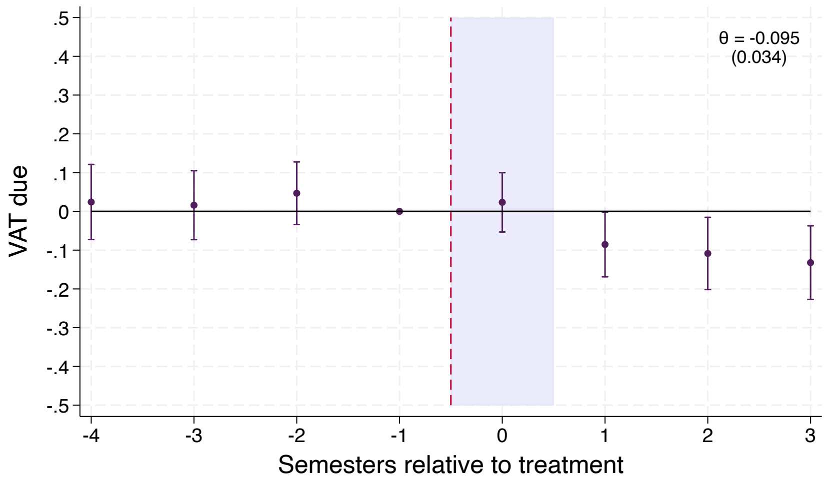
Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures is the suppliers of large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.2. Spillover effects on individually owned firms. 20% Threshold

Share of total sales = At least 20%



(a) Output VAT

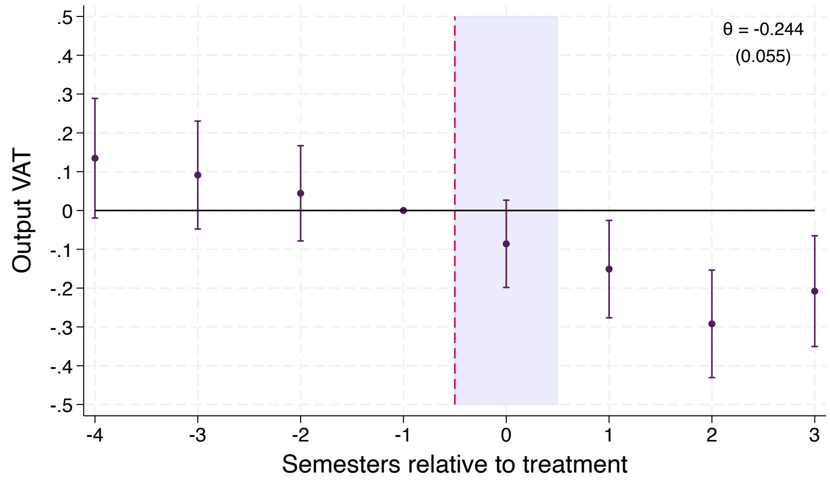


(b) VAT due

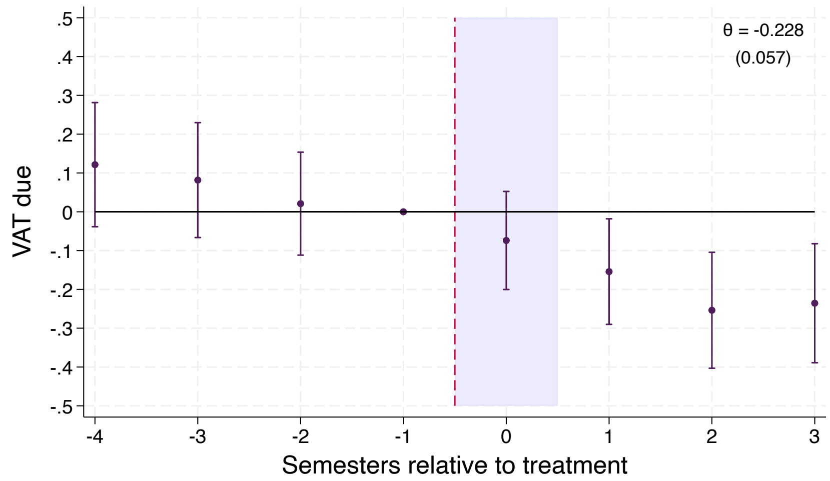
Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures is the suppliers of large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.3. Spillovers effects on individually owned firms. Control group 2

Share of total sales = At least 40%



(a) Output VAT

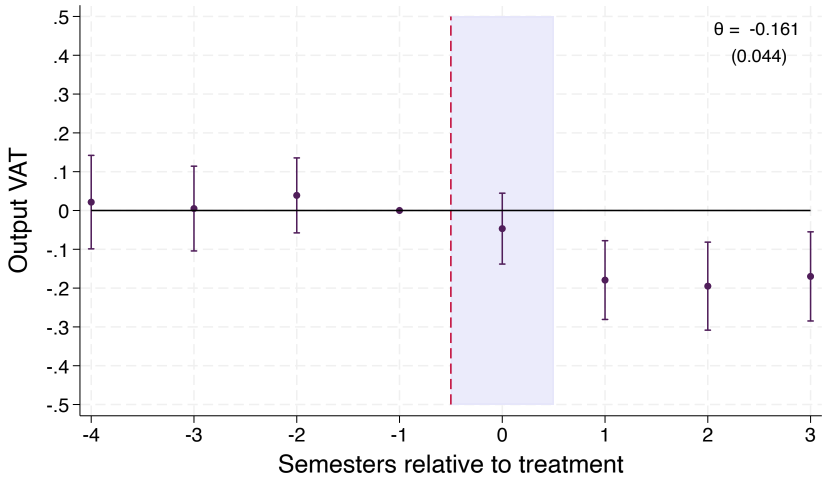


(b) VAT due

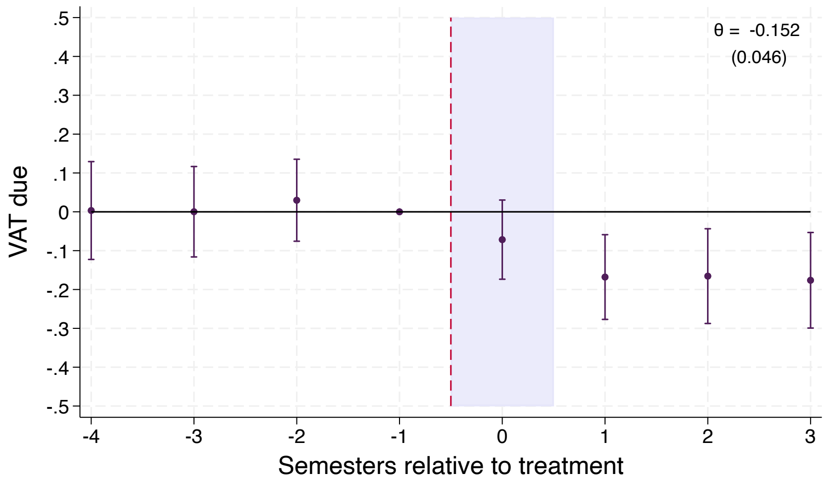
Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures is the suppliers of firms selected as special taxpayers in 2021. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.4. Spillover effects of monitoring large taxpayers on individually owned firms. Robustness check

Share of total sales = At least 40%



(a) Output VAT

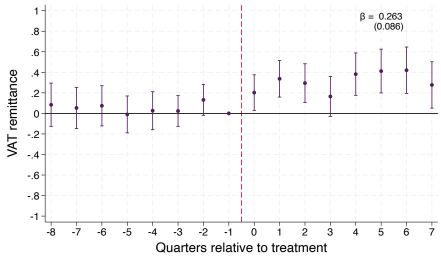


(b) VAT due

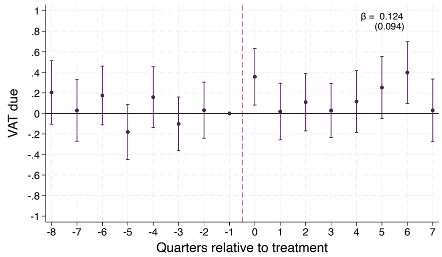
Notes: These plots show the dynamic effects of the selection of a client on their suppliers. The effects were estimated using Equation 2.3. The control group used in the figures consists of suppliers to large firms. The empirical analysis uses semester panel data and includes firm fixed effects and time fixed effects. The time window covers 4 semesters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.5. Robustness: 70th–30th percentile definition of exposure

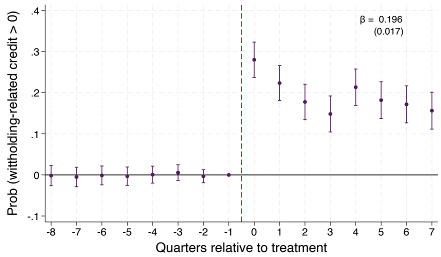
Differences in differences estimates
Treated group: Firms with exposure above the 70th percentile
Control group: Firms with exposure below the 30th percentile



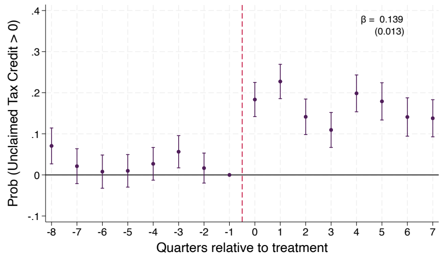
(a) VAT remittance



(b) VAT due



(c) Probability of reporting a withholding-related tax credit

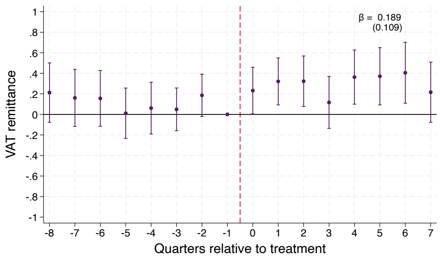


(d) Probability of reporting an unclaimed tax credit

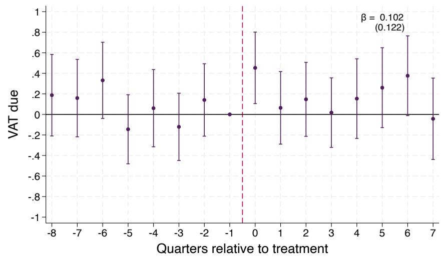
Notes: These plots show the dynamic effects of the introduction of withholding between large taxpayers in 2015. The effects were estimated using Equation 2.4, and I exploit variation from the intensive margin of the reform. The empirical analysis uses quarterly panel data and includes firm and time fixed effects. The dependent variables are transformed using the hyperbolic sine function, after adjusting all monetary values to 2018 prices. The time window covers 8 quarters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.6. Robustness: 80th–20th percentile definition of exposure

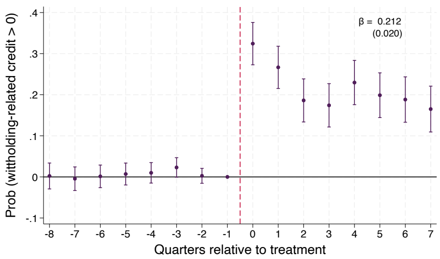
Differences in differences estimates
Treated group: Firms with exposure above the 80th percentile
Control group: Firms with exposure below the 20th percentile



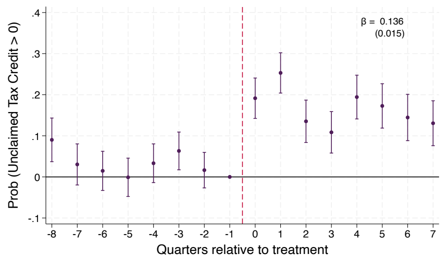
(a) VAT remittance



(b) VAT due



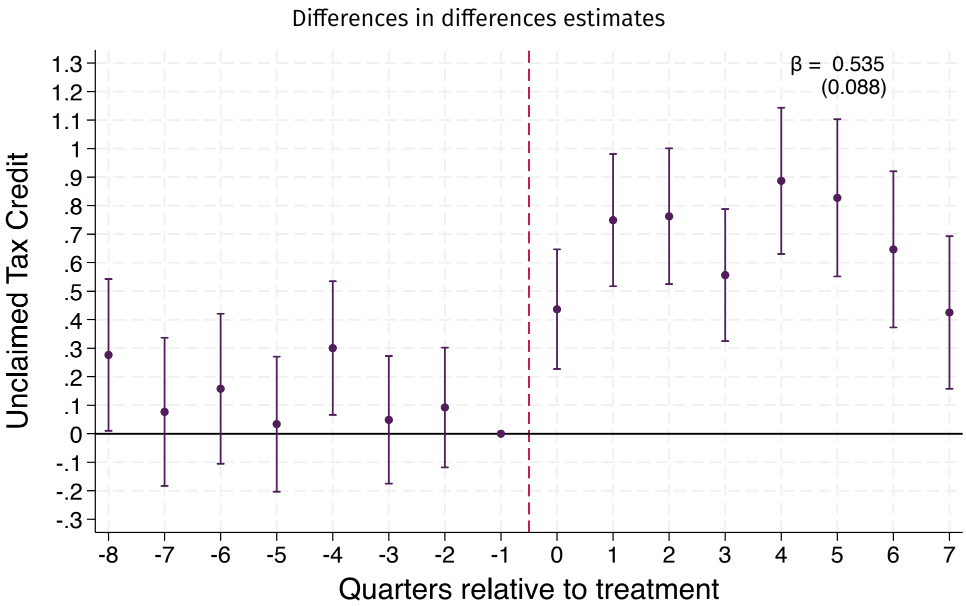
(c) Probability of reporting a withholding-related tax credit



(d) Probability of reporting an unclaimed tax credit

Notes: These plots show the dynamic effects of the introduction of withholding between large taxpayers in 2015. The effects were estimated using Equation 2.4, and I exploit variation from the intensive margin of the reform. The empirical analysis uses quarterly panel data and includes firm and time fixed effects. The dependent variables are transformed using the hyperbolic sine function, after adjusting all monetary values to 2018 prices. The time window covers 8 quarters before and after treatment. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

Figure 2.A.7. Effects of the 2015 reform on unrefunded balance



Notes: These plots show the dynamic effects of the introduction of withholding between large taxpayers in 2015. The effects were estimated using Equation 2.4, and I exploit variation from the intensive margin of the reform. The empirical analysis uses quarterly panel data and includes firm fixed effects and time fixed effects. The time window covers 8 quarters before and after treatment. The dependent variable is log-transformed, after adjusting all monetary values to 2018 prices. Estimated coefficients are shown as dots, and the vertical lines denote their 95% confidence intervals. Standard errors are clustered at the firm level. Return to the main text.

2.B Additional Tables

Table 2.B.1. Descriptive Statistics. 30% Threshold

All variables expressed in 2018 USD (thousands)
Second semester of 2017

	Panel A. All suppliers					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	76.96	(288.06)	46.26	(176.60)	50.60	(189.26)
Taxable purchases	52.23	(250.37)	29.42	(129.99)	30.49	(129.59)
Output VAT	9.23	(34.57)	5.55	(21.19)	6.07	(22.71)
Input VAT	6.27	(30.04)	3.53	(15.60)	3.66	(15.55)
VAT due	4.76	(14.92)	2.95	(10.18)	3.40	(13.39)
Observations	5,332		22,466		4,979	

	Panel B. Individually owned firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	23.58	(28.34)	21.20	(27.93)	21.41	(29.50)
Taxable purchases	10.42	(20.04)	9.50	(22.64)	9.39	(20.23)
Output VAT	2.83	(3.41)	2.54	(3.35)	2.57	(3.54)
Input VAT	1.25	(2.40)	1.14	(2.72)	1.13	(2.43)
VAT due	1.89	(2.38)	1.67	(2.34)	1.73	(2.42)
Observations	3,922		17,858		3,880	

	Panel C. Corporate firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	226.008	(531.60)	143.96	(371.42)	155.60	(383.95)
Taxable purchases	169.02	(467.27)	106.69	(270.54)	104.41	(261.26)
Output VAT	27.13	(63.79)	17.28	(44.57)	18.67	(46.07)
Input VAT	20.28	(56.07)	12.80	(32.46)	12.53	(31.35)
VAT due	12.77	(27.24)	7.88	(21.34)	9.42	(27.50)
Observations	1,405		4,578		1,084	

Notes: This table reports descriptive statistics at the supplier level. The treated group consists of suppliers to special taxpayers selected in February 2018, whose sales to these firms represented at least 30% of their total sales during the second semester of 2017. The control groups include: (i) suppliers to special taxpayers selected in 2021, and (ii) large non–special taxpayer firms with comparable levels of client dependency. Panel A reports statistics for all suppliers. Panel B focuses on suppliers that are individually owned firms, while Panel C reports statistics for corporate suppliers. The total number of suppliers in Panel A slightly exceeds the sum of Panels B and C because it also includes taxpayers classified under the *Economía Popular y Solidaria* (e.g., associations). Return to the main text.

Table 2.B.2. Descriptive Statistics. 20% Threshold

All variables expressed in 2018 USD (thousands)
Second semester of 2017

	Panel A. All suppliers					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	78.82	(274.76)	48.65	(181.69)	51.45	(182.57)
Taxable purchases	54.08	(238.04)	32.12	(138.46)	32.39	(133.69)
Output VAT	9.46	(32.97)	5.84	(21.80)	6.17	(21.91)
Input VAT	6.49	(28.57)	3.85	(16.62)	3.89	(16.04)
VAT due	4.73	(14.08)	2.95	(10.23)	3.34	(12.45)
Observations	6,770		25,192		6,401	

	Panel B. Individually owned firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	23.86	(28.73)	20.93	(27.53)	21.21	(27.93)
Taxable purchases	11.03	(20.40)	9.89	(22.40)	9.75	(19.16)
Output VAT	2.86	(3.45)	2.51	(3.30)	2.55	(3.35)
Input VAT	1.32	(2.45)	1.19	(2.69)	1.17	(2.30)
VAT due	1.86	(2.39)	1.61	(2.28)	1.66	(2.30)
Observations	4,884		19,923		4,891	

	Panel C. Corporate firms					
	Treated suppliers		**Control Group 1**		**Control Group 2**	
	Mean	SD	Mean	SD	Mean	SD
Taxable sales	221.71	(491.44)	154.14	(376.73)	150.93	(357.08)
Taxable purchases	165.88	(430.94)	116.26	(284.99)	105.33	(261.05)
Output VAT	26.61	(58.97)	18.50	(45.21)	18.11	(42.85)
Input VAT	19.91	(51.71)	13.95	(34.20)	12.64	(31.33)
VAT due	12.18	(24.94)	8.00	(21.24)	8.86	(24.66)
Observations	1,880		5,233		1,493	

Notes: This table reports descriptive statistics at the supplier level. The treated group consists of suppliers to special taxpayers selected in February 2018, whose sales to these firms represented at least 30% of their total sales during the second semester of 2017. The control groups include: (i) suppliers to special taxpayers selected in 2021, and (ii) large non–special taxpayer firms with comparable levels of client dependency. Panel A reports statistics for all suppliers. Panel B focuses on suppliers that are individually owned firms, while Panel C reports statistics for corporate suppliers. The total number of suppliers in Panel A slightly exceeds the sum of Panels B and C because it also includes taxpayers classified under the *Economía Popular y Solidaria* (e.g., associations). Return to the main text.

Table 2.B.3. First stage of selection of a client as special taxpayer

	Withholding (1)	**Probability withholding related credit (2)**
θ	1.758*** (0.133)	0.160*** (0.014)
Mean Dep Variable in k = -1	USD 2,182	47%
Observations	38,804	38,804

Notes: This table presents the effects of the selection of special taxpayers on their suppliers. Estimates are from a difference-in-differences specification following Equation 2.2. Outcome variables are transformed using the hyperbolic sine transformation to handle zeros. Monetary variables are adjusted for inflation using 2018 prices. The specifications include firm and time fixed effects. Standard errors are clustered at the firm level.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Return to the main text.

Table 2.B.4. Effects of the selection of special taxpayers on individually owned firms. Different thresholds

(a) *Share of total sales = At least 40%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.164***	-0.020	-0.159***
	(0.043)	(0.038)	(0.044)
Mean Dep Var in (t–1)	2,558	1,077	1,753
Observations	141,703	141,703	141,703
R-squared	0.458	0.724	0.463

(b) *Share of total sales = At least 30%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.132***	0.006	-0.131***
	(0.038)	(0.034)	(0.040)
Mean Dep Var in (t–1)	2,543	1,140	1,687
Observations	162,525	141,703	162,525
R-squared	0.500	0.727	0.463

(c) *Share of total sales = At least 20%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.101**	-0.012	-0.094**
	(0.033)	(0.030)	(0.034)
Mean Dep Var in (t–1)	2,512	1,187	1,615
Observations	185,522	185,522	185,522
R-squared	0.462	0.729	0.467

Notes: Estimates are from a difference-in-differences specification with firm and time fixed effects. Outcome variables are transformed using the hyperbolic sine transformation. Monetary values are deflated to 2018 prices. Standard errors are clustered at the firm level. *Significance levels:* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Return to the main text.

Table 2.B.5. Effects of the selection of special taxpayers on individually owned firms. Control group 2

(a) *Share of total sales = At least 40%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.244***	-0.079	-0.228***
	(0.055)	(0.049)	(0.057)
Mean Dep Var in (t-1)	2,560	1,074	1,767
Observations	48,303	48,303	48,303
R-squared	0.453	0.721	0.454

(b) *Share of total sales = At least 30%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.213***	-0.051	-0.201***
	(0.044)	(0.049)	(0.051)
Mean Dep Var in (t-1)	2,569	1,127	1,727
Observations	58,180	58,180	58,180
R-squared	0.457	0.721	0.457

(c) *Share of total sales = At least 20%*

	Output VAT (1)	**Input VAT** (2)	**VAT due** (3)
θ	-0.182***	-0.058	-0.159***
	(0.042)	(0.038)	(0.043)
Mean Dep Var in (t-1)	2,545	1,170	1,660
Observations	73,401	73,401	73,401
R-squared	0.459	0.722	0.460

Notes: This table presents the effects of the selection of special taxpayers on their suppliers. Estimates are from a difference-in-differences specification following Equation 2.2. Outcome variables are transformed using the hyperbolic sine transformation to handle zeros. Monetary variables are adjusted for inflation using 2018 prices. The specifications include firm and time fixed effects. Standard errors are clustered at the firm level. *Significance levels:* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Return to the main text.

Table 2.B.6. Effects of the selection of special taxpayers on corporate suppliers

Share of total sales = At least 40%

	Output VAT	Input VAT	VAT due
θ	-0.209**	-0.132*	-0.157
	(0.103)	(0.083)	(0.102)
Mean Dep Var in (t–1)	16,490	11,959	8,071
Observations	38,804	38,804	38,804
R-squared	0.504	0.604	0.501

Notes: Estimates are from a difference-in-differences specification with firm and time fixed effects. Outcome variables are transformed using the hyperbolic sine transformation. Monetary values are deflated to 2018 prices. Standard errors are clustered at the firm level. *Significance levels:* $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.B.7. Robustness: 70th–30th percentile definition of exposure

Treated group: Firms with exposure above the 70th percentile
Control group: Firms with exposure below the 30th percentile

	VAT remittance (1)	VAT due (2)	Probability of withholding related credit (3)	Probability of reporting unclaimed tax credit (4)
High exposure x Post	0.263***	0.124	0.196***	0.139***
	(0.086)	(0.094)	(0.017)	(0.013)
Mean Dep Variable in q=-1 (USD thousands)*	210	84	0.12	0.571
Observations	33,187	33,187	33,187	33,187

Notes: This table presents the effects of the implementation of withholding between special taxpayers in 2015. Estimates are from a differences in differences specification following Equation 2.4. All outcome variables are expressed in logs, after adjusting for inflation using 2018 prices and adding one to handle zeros. The specifications include firm and time fixed effects. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Return to the main text.

Table 2.B.8. Robustness: 80th–20th percentile definition of exposure

Treated group: Firms with exposure above the 80th percentile
Control group: Firms with exposure below the 20th percentile

	VAT remittance (1)	VAT due (2)	Probability of withholding related credit (3)	Probability of reporting unclaimed tax credit (4)
High exposure x Post	0.189*	0.102	0.212***	0.138***
	(0.109)	(0.122)	(0.020)	(0.015)
Mean Dep Variable in q=-1 (USD thousands)*	216	69	0.114	0.571
Observations	22,049	22,049	22,049	22,049

Notes: This table presents the effects of the implementation of withholding between special taxpayers in 2015. Estimates are from a differences in differences specification following Equation 2.4. All outcome variables are expressed in logs, after adjusting for inflation using 2018 prices and adding one to handle zeros. The specifications include firm and time fixed effects. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Return to the main text.

2.C Data Appendix

2.C.1 Variable Definitions

Purchases Annex
(Anexo Transaccional Simplificado, ATS)

- Trade: It includes the transactions that are categorized as purchases of goods, services, fixed assets, inventories, and health expenses. These transactions correspond to the following codification of tax credit in ATS: 01, 02, 03, 04, 06, 07 and 09. I exclude invoices issued abroad, dividends and rent payments, transactions made by the employees of the firm that are covered by the firm, presumptive withholding, sales receipts issued for the purchases of second-hand cars and movable property, and cash register receipts. These transactions correspond to the following codification of transaction documents: 15, 19, 41, 42, 47, 48, 344, 5. Finally, for each client-supplier-month, I add the traded amount subject to 12% VAT, 0% VAT, and exempted from VAT.[24]
- Taxable trade: I follow the same restrictions explained for the construction of the trade variable. However, I only consider the transactions subject to 12% VAT.

Value-added tax Returns
(Formulario 104)

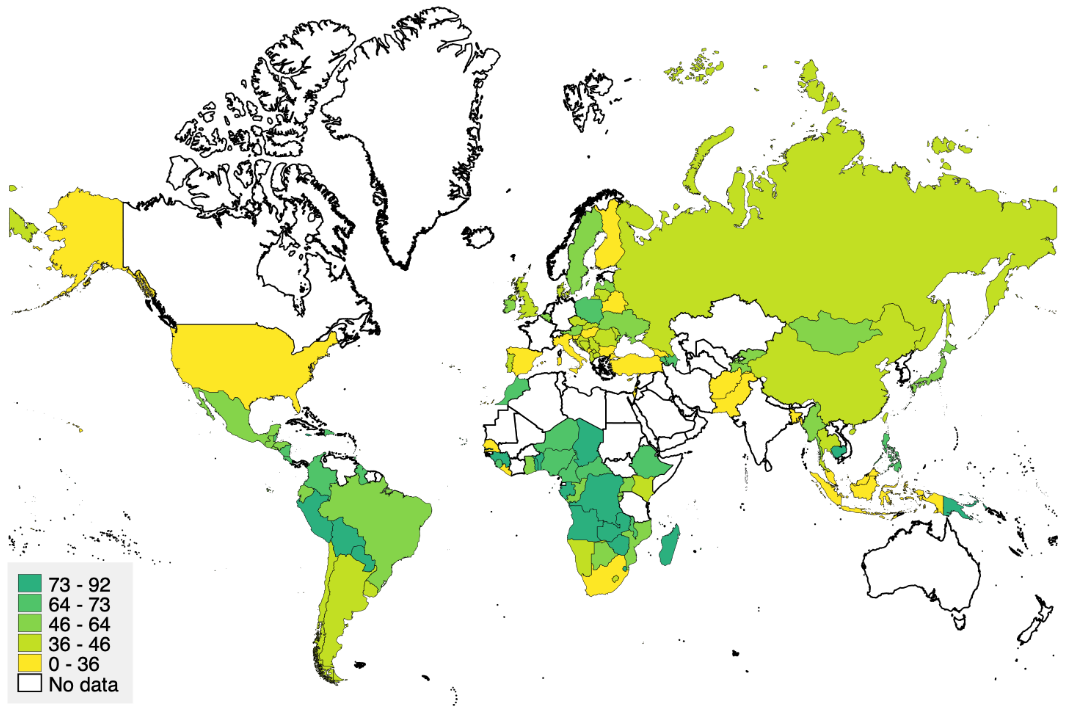
- Sales and exports: Reports the total net sales and exports (credit notes are deducted).
- Taxable sales: Sales that are subject to VAT, computed as the output VAT/ VAT rate.
- Output VAT: VAT paid on sales.
- Purchases and imports: Total net purchases and imports (credit notes are deducted).
- Taxable purchases: Purchases that are subject to VAT, computed as the input VAT/ VAT rate.
- Input VAT: VAT paid on the purchases of goods, services, and imports.
- VAT due: This is the difference between the Output VAT and Input VAT.
- Tax credit in the current month: If the difference between the output VAT and the input VAT is negative, the taxpayer reports a tax credit for the current month.

24. Transactions that are credit notes are deducted from the total amount purchased from a supplier (They are denoted by transaction document number 4).

- Tax credit in the previous month (Unclaimed tax credits): This is the tax credit that was not used in the previous month. A positive balance reflects that the input VAT was higher than the output VAT or that the VAT withheld by clients was higher than the VAT due.
- VAT withheld by clients: The amount of VAT withheld by clients from the taxpayer's sales (see Section 2.2.1).
- VAT withheld from suppliers: The total amount of VAT that the taxpayers have withheld from suppliers.
- VAT liability: Calculated as VAT due (output VAT - input VAT) minus tax credit from the previous month and the VAT withheld by clients.
- Effective tax rate: The ratio of VAT liability to taxable sales.
- VAT remittance: VAT liability if it is positive, or the reported VAT credit if the liability is zero.

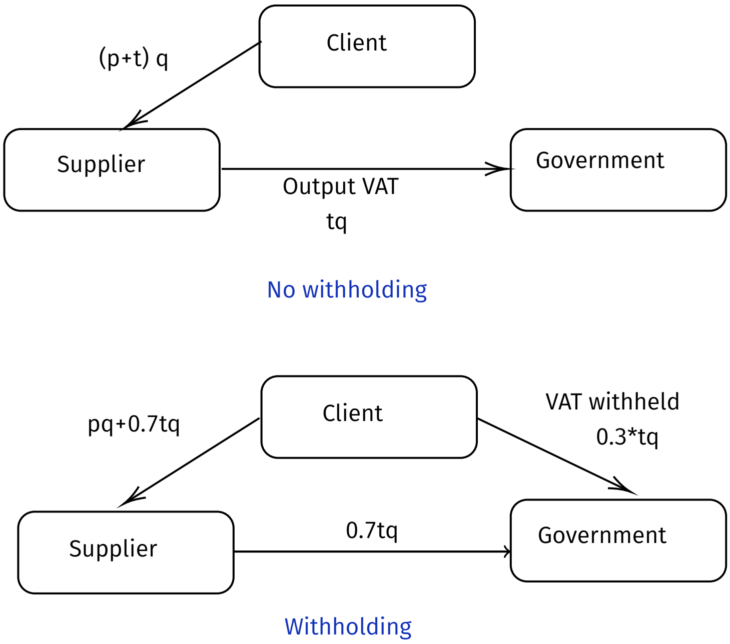
2.D Additional Information

Figure 2.C.1. Percentage of Revenue Collected from Large Taxpayers, 2018



Notes: This figure shows the percentage of total net revenue collected from large taxpayers in 2018 and uses information from CIAT, IOTA, IMF, OECD, and the International Survey on Revenue Administration, https://data.rafit.org. The survey was conducted in 159 countries. Further, 19 countries did not have any large taxpayer program or office, and 12 countries that have a large taxpayer program did not report information on the percentage of revenue collected from this group. The designation of a taxpayer as a large taxpayer is based on the definition of each country. Return to the main text.

Figure 2.C.2. VAT withholding: An Example



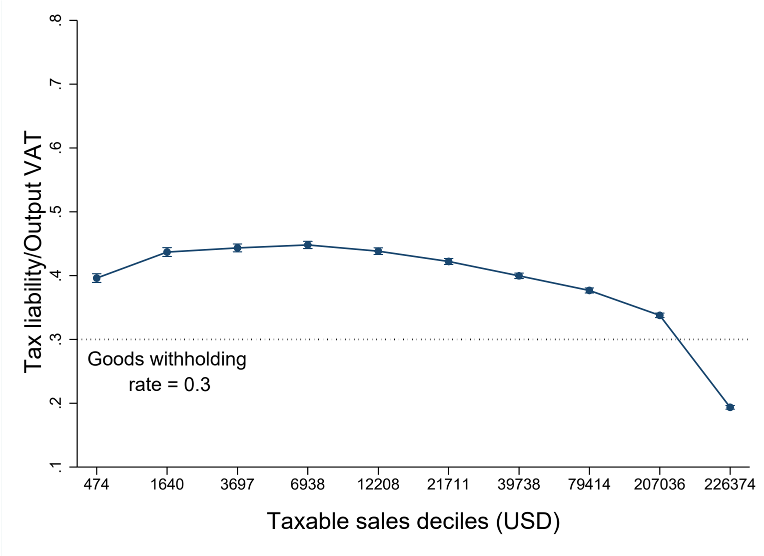
Notes: This figure illustrates the process of VAT withholding using a simple example of a transaction between a client and a supplier. For simplicity, I assume that the supplier does not purchase any inputs during the production process and, consequently, does not claim an input VAT. The client buys a quantity q of the input at a price p and pays VAT of t. The tax liability of the supplier is tq, which he remits to the government. When reverse VAT withholding is implemented, the client remits a % of tax directly to the government, in this example 30%, ($0.3 * tq$) on behalf of the supplier. The remaining 70% ($0.7 * tq$) is remitted directly by the supplier. Return to the main text.

Table 2.D.1. VAT Withholding Rates in Ecuador

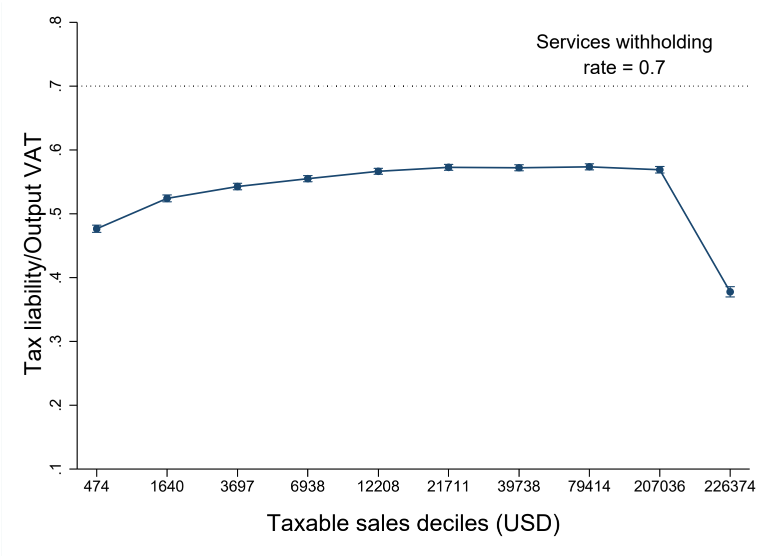
Client	Supplier Special Taxpayers	Firm and sole proprietorship mandated to keep accounting records	Sole proprietorship not mandated to keep accounting records
Special Taxpayers	Goods: 10% Services: 20% Construction: 30%	Goods: 30% Services: 70% Construction: 30%	Goods: 30% Services: 70% Construction: 30%
Firm and sole proprietorship mandated to keep accounting records	-	-	Goods: 30% Services: 70% Construction: 30%
Sole proprietorship not mandated to keep accounting records	-	-	-

Notes: This table provides an overview of the VAT withholding rates applicable for the transactions between clients and suppliers. Withholding between special taxpayers was introduced in June 2015 for goods and services, while the construction sector has always been subject to a 30% withholding rate. Other withholding agents besides the special taxpayers are public sector institutions, insurance companies, credit card companies, and regular exporters. A withholding rate of 100% applies to professional services and rental of properties when the supplier is not mandated to keep accounting records. The taxpayers that are not subject to withholding are the public sector, airlines, travel agencies on the sale of plane tickets, fuel distribution, and retail. Since June 2015, withholding does not apply to financial institutions, credit card companies, newspaper distributors, and regular exporters. There are specific rules for fuel distribution and retail and for tour operators that can be consulted in *Resolución No. NAC-DGERCGC15-284*, published in March 2015. Return to the main text.

Figure 2.C.3. VAT liability as share of output VAT



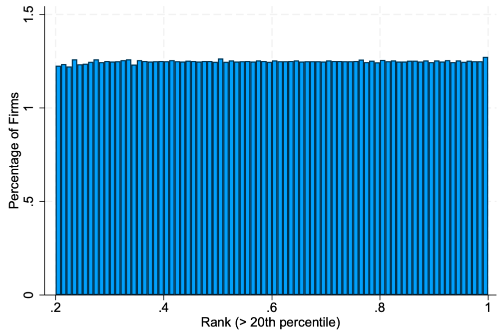
(a) Goods



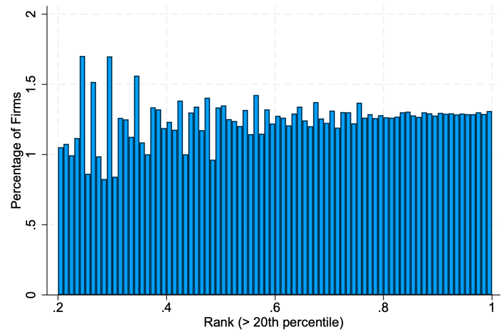
(b) Services

Notes: This figure plots the VAT (net) liability as a share of the output VAT for goods (Panel A) and services (Panel B) across the taxable sales distribution. In the case of services, the VAT liability relative to output VAT is below the 70% withholding rate. This suggests that the withholding rate may be set too high, potentially leading to excessive tax credit claims and refund requests. The graph presents data from 2014. Return to the main text.

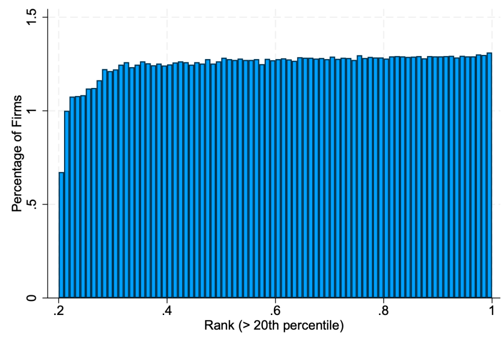
Figure 2.C.4. Distribution of Percentile Rankings: Evidence of Bunching?



(a) Revenues



(b) Partners



(c) Taxes

Notes: These plots show the distribution of the percentile provincial rankings of revenues, trade partners, and taxes (including VAT withheld). Return to the main text.

Chapter 3

A Machine Learning Approach to Selecting Large Firms for Tax Monitoring Programs *

This paper studies whether machine learning methods can be applied to select large firms for tax monitoring programs. In the context of the Special Taxpayer Program in Ecuador and using administrative tax data, I train predictive models to estimate two target outcomes of the program: VAT liabilities of a firm and VAT liabilities of its suppliers observed through reported transactions. I compare the performance of a Random Forest model to Lasso, Elastic Net, and a naive benchmark that predicts the average VAT liability for all firms. The Random Forest Model has the best performance among the other models for forecasting firms' own VAT liabilities. Ranking the firms based on their predicted VAT liabilities and comparing the top-ranked firms with those with the highest actual liabilities shows that the model correctly identifies half of the top firms. These initial evidence suggests that the predictive models should be refined before implementing them for the selection of special taxpayers.

* I would like to thank Arthur Seibold, Eckhard Janeba and seminar participants in the Public Economic Seminar at the University of Mannheim for their valuable comments and suggestions. I am grateful to the Servicio de Rentas Internas of Ecuador (SRI) for providing access to tax administrative data. I also thank Christian Chicaiza and Maria Leonor Oviedo from SRI for their assistance with the data and for facilitating my research visits.

3.1 Introduction

Building tax capacity depends on the state's ability to identify taxpayers, determine their true tax liabilities, and collect those liabilities (Okunogbe, 2023; Okunogbe and Tourek, 2024). Because firms contribute to all three dimensions, they are particularly important for the tax administration. First, firms remit the majority of tax revenues, whether through their own payments or amounts withheld from employees and trade partners (Kopczuk and Slemrod, 2006). Second, they generate third-party information that the tax authority can use to identify smaller suppliers and assess those suppliers' economic activity and tax liabilities. Third, firms collect taxes through withholding mechanisms (e.g., Garriga and Tortarolo, 2024). The government especially depends on large firms (Boning and Slemrod, 2018), and to protect the tax revenue, tax authorities often include them in special tax monitoring programs (Baer et al., 2002). Their contribution to the identification, detection, and collection capacities of the government help explain why they are targets of enforcement strategies.

Large taxpayers programs are common across many countries.[1] According to the International Survey on Revenue Administration, conducted by CIAT, IOTA, IMF and OECD, 143 countries have such programs, representing 73% of the total number of countries in the world with monitoring programs for large firms. International organizations recommend selecting firms for these programs using size-based indicators such as annual sales or turnover, annual income, assets, trade volumes (Baer et al., 2002). These indicators are often combined with specific thresholds to classify firms as large taxpayers (CIAT/AEAT/IEF, 2018). This paper studies whether tax administrations can improve this selection process by using machine learning methods to identify firms that are the most relevant for tax revenue collection. Although the first-best solution would be to monitor all firms, budget constraints require governments to target enforcement policies. Considering these constraints and the widespread adoption of large taxpayer programs, it is important to study how firms are selected for monitoring.

A machine learning approach offers several advantages over traditional selection methods based on firm size. First, machine learning can improve the accuracy of the selection by applying more flexible functional forms and using a large number of firm and supplier characteristics.[2] This is particularly relevant for tax administrations, which routinely collect a large volume of administrative data about taxpayers. Second, tax administrations around the world have been adopting machine learning approaches into their operations. A recent report of the OECD documents that,

1. Countries typically establish either large taxpayer offices (LTOs) or large taxpayer programs. For simplicity, I refer to both as large taxpayer programs throughout this paper.

2. Kleinberg et al. (2015) mention the use of a wide range of variables and flexible forms between them as an advantage of machine learning.

by 2021, 54% of tax administrations had already implemented machine learning tools for risk assessment and fraud detection, and 28% were in the process of implementation (OECD, 2023). Third, thresholds based on firm size are susceptible to manipulation. For example, Almunia and Lopez-Rodriguez (2018) show that Spanish firms adjust their reported revenues to stay below the cutoff that determines the inclusion in large taxpayer programs.

The analysis of this paper focuses on Ecuador's Special Taxpayer Program, a type of large taxpayer program through which the government designates large firms as priority targets for tax monitoring and assigns them VAT withholding responsibilities. Therefore, the program targets the VAT liabilities of both the selected firms and their suppliers. The current selection into the program is based on provincial rankings of indicators that reflect firm size, such as sales, purchases, tax liabilities, and number of trading partners (Oliva and Aparicio, 2010; De Simone, 2022). To link the selection of firms to the program's objectives, I consider the government's problem as a prediction exercise with two targets: 1. the VAT liability of the firm itself, and 2. the VAT of its suppliers observed through their reported transactions with the firm. For the second prediction target, I only consider suppliers that are not themselves designated as special taxpayers, as these are the firms whose VAT outcomes are most likely to be affected by a client's designation as a special taxpayer. This target corresponds to the input VAT of the non-monitored suppliers reported by the corresponding clients on firm-to-firm transaction data.

Large taxpayer programs are implemented to protect tax revenue (Baer et al., 2002). In line with this goal, the government can pursue two policy objectives: (a) maximize the volume of monitored tax payments/transactions, and (b) maximize additional tax revenue. This study speaks to the first objective by focusing on predicted VAT outcomes of the targeted large firm and the suppliers. Predicting treatment effects, which would address the second objective, is an important area of future research.

The empirical analysis begins by building prediction models for firm-level and supplier-level VAT liabilities using administrative tax data. The goal of these exercises is to assess whether machine learning methods, specifically a Random Forest model, can accurately predict these outcomes. I compare its performance to three benchmark approaches: Lasso, Elastic Net, and a naive model that assigns the mean of the outcome variable to all firms (Baseline Moel). Model performance is evaluated using the root mean square error (RMSE). As a starting point, I use the earliest available data, combining predictor variables from 2013 with VAT outcomes from 2014. I use nested cross-validation to assess the out-of-sample performance of the models.

I find that the Random Forest model has the lowest average RMSE when predicting the taxpayer's VAT liability and outperforms the benchmark models. However, its improvement with respect to the naive model, measured as the reduction of the RMSE, is modest and equal to 35%. In contrast, the Random Forest performs worse than the benchmark models when predicting the input VAT of non-monitored suppliers. This result indicates that there is room to improve the current model before using it for this type of prediction task. Considering these findings, I now continue the analysis with the model for predicting the taxpayer's own VAT liability and test its performance using a dataset that combines predictor variables from 2014 with VAT outcomes from 2015. I find that the improvement of the model with respect to the naive prediction drops to 28%, and the model only explains 49% of the variation of the VAT liabilities, as measured by the R^2.

To further test the model's performance and better understand the firm's behavior over time, I extend the prediction exercise by combining two years of data: 2013 predictors with 2014 VAT outcomes, and 2014 predictors with VAT 2015 outcomes. This approach reduces the dependence of the prediction on a single year. Once again, I find that the Random Forest model achieves the lowest average RMSE and the best performance among the alternatives. I then apply the trained model to firm characteristics from 2017 to generate predictions of VAT liabilities in 2018. Based on these predicted values, I rank firms within each province. Because I observe the number of firms actually selected into the Special Taxpayer Program by province in 2018, I use this information to select the top-ranked firms in each province according to the predicted VAT liability. I then compare this predicted selection to the actual firms that had the highest VAT liability in 2018 and compute a measure of recall by province. On average, the model correctly identifies 57% of the top firm. Ideally, one would want the model to be able to rank correctly more firms; therefore, this limitation motivates future research to refine the predictive models.

This paper contributes to the growing body of literature that applies machine learning to the design of policies. Recent studies have shown how predictive algorithms can support government programs across different fields, including identifying corrupt municipalities (Ash et al., 2025), identifying the beneficiaries of social programs (Aiken et al., 2023; Aiken et al., 2022), improving the targeting of energy efficiency programs (Christensen et al., 2024), and the targeting of workplace inspections (Johnson et al., 2023).

The implementation of machine learning approaches is also expanding to analyze topics related to the tax administration. Prior research has studied its application to detect tax evasion (Battaglini et al., 2024; González-Martel et al., 2020; Tuyishimire and Murorunkwere, 2024), to analyze the fairness of audit strategies (Black et al., 2022), to study VAT compliance gaps (Ebrahim et al., 2024), to estimate property values for tax purposes (Bergeron et al., 2023), and to target beneficiaries for a tax rebate program (Andini et al., 2018). The main contribution of this paper is to investigate whether machine learning can be used for selecting firms into a large taxpayer program. To the best of my knowledge, there is no previous research studying the selection to these programs.

As mentioned before, the empirical strategy of this chapter focuses on maximizing the volume of tax payments that can be monitored. Studying selection rules aimed to recover the largest additional tax revenue at the least cost is left for future work. Related to this point, it is important to mention that earlier theoretical literature concludes that, under the optimal audit policy, taxpayers who report low incomes are audited. For instance, Reinganum and Wilde (1985) derive the threshold that induces truthful reporting at the least cost and argue that the government should audit low reported incomes exclusively. In the optimal audit policy described by Sánchez and Sobel (1993), the income distribution is divided into at most 3 groups, where the lowest income group is audited with high probability, the middle income group is audited with positive probability, and the highest income group is not audited. These results seem difficult to reconcile with the motivations for establishing a large taxpayer program. However, in a more recent paper, Boning et al. (2025) estimate audit returns at different parts of the income distribution and find that auditing top-income taxpayers brings higher returns per dollar spent than auditing taxpayers with income below the median. These findings would support shifting the focus of monitoring to large taxpayers. Since the three papers mainly discussed income reported by individuals, a promising area for future work is to estimate the returns to auditing firms of different sizes and contrast these results with the motivations for implementing large taxpayer programs.

The remainder of the paper is structured as follows. Section 3.2 presents a stylized model that explains the government's problem. Section 3.3 describes the data sources and sample construction. Section 3.4 presents the research design, and Section 3.5 discusses the results. Finally, section 3.6 concludes.

3.2 The Stylized Government's Problem

3.2.1 Policy Goals

In the stylized problem discussed in this section, the government selects firms for a large taxpayer program to maximize the amount of tax revenue it can monitor. This policy goal is in line with the arguments of Baer et al. (2002), who argue that monitoring large taxpayers can protect the revenue base of the government, especially in developing countries, because a small number of these firms contribute a large share of tax revenue through their tax liabilities and taxes withheld from other taxpayers. Therefore, when selecting firms for monitoring, the government considers the tax liabilities of the large firms and the taxes of the trade partners, as observed in the transactions reported by the large firms.

An alternative policy goal of the government would be to select firms to maximize the causal effect of the program on total tax revenue. I discuss these two alternatives in section 3.2.3.

3.2.2 Overview

Each month, a taxpayer purchases inputs from suppliers and sells final goods or services to clients. The taxpayer is responsible for collecting the VAT on sales (output VAT) and receives VAT invoices on purchases (input VAT). In the following month, the taxpayer remits the VAT liability to the government, which is calculated as the difference between output VAT and input VAT.[3]

Due to budget constraints, the government can monitor only a limited number of taxpayers. Following international practice, it allocates a share of its monitoring resources to large firms (Bachas et al., 2019). As a result, the selection of firms for the program becomes an important component of the enforcement strategy.

3.2.3 Government's Problem

At the start of period t, the tax authority observes the following information for each firm i in a population of n firms:

- *Balance-sheet characteristics* from the most recent tax returns:

$$X_{i,t-1} \quad = \quad \left(\text{revenue}_{i,t-1},\ \text{liabilities}_{i,t-1},\ \text{assets}_{i,t-1}, \ldots\right),$$

- *Network characteristics* from transactional annexes:

$$N_{i,t-1} \quad = \quad \left(\#\ \text{suppliers}_{i,t-1},\ \text{supplier types}_{i,t-1}, \ldots\right).$$

Based on this information, the government selects J firms for monitoring. Selecting a firm i in period t allows the government to monitor its VAT liability and the VAT on invoices issued by i's suppliers to i.[4] Let $y_{i,t}^{\text{base}}$ denote the baseline monitorable VAT for firm i (the sum of i's VAT liability and VAT on transactions with suppliers in period t). Because $y_{i,t}^{\text{base}}$ is not observed at the beginning of period t, the government makes a prediction, $\hat{y}_{i,t}^{\text{base}} = \mathbb{E}[y_{i,t}^{\text{base}} \mid X_{i,t-1}, N_{i,t-1}]$, using observed characteristics, $X_{i,t-1}$, and network characteristics, $N_{i,t-1}$.

Once the government computes $\hat{y}_{i,t}^{\text{base}}$, its objective is to select the taxpayers that would allow it to monitor the largest amount of tax revenue. The problem framing is similar to Black et al. (2022), who discuss a revenue-optimal audit allocation. In their setting, the government selects the taxpayers with the highest ratio of revenue returned to the tax agency relative to audit costs. In contrast, my framework focuses on taxpayers who contribute the largest tax revenue that can be monitored.

3. Taxpayers can also use their unrefunded VAT credits from previous periods to offset their current VAT liabilities.

4. The VAT on transactions with suppliers can also be observed in firm-to-firm trade annexes reported by firm i.

$$\max_{j_{i,t}\in\{0,1\}} \sum_{i=1}^{n} j_{i,t}\hat{y}_{i,t}^{\text{base}} \tag{3.1}$$

subject to

$$\sum_{i=1}^{n} j_{i,t} = J \tag{3.2}$$

The government selects the J firms with the largest predicted baseline monitorable VAT, $\hat{y}_{i,t}^{\text{base}}$. Thus,

$$j_{i,t} = \begin{cases} 1, & \text{if } \hat{y}_{i,t}^{\text{base}} \text{ is among the top } J, \\ 0, & \text{otherwise.} \end{cases}$$

The government can use proxies of firm size to approximate $\hat{y}_{i,t}^{\text{base}}$, or it can use machine learning algorithms for the prediction using information on $X_{i,t-1}$ and $N_{i,t-1}$.

This policy objective ranks firms by predicted baseline monitorable VAT but does not consider the causal effect of selection on the VAT. Instead of maximizing the amount of tax revenue that can be monitored, the government may want to select the taxpayers that would bring the highest additional tax revenue. This alternative objective would incorporate the causal effect of the selection.

For example, one can define the causal effect of the selection on VAT revenue as $r_{i,t} = \mathbb{E}[y_{i,t}(1) - y_{i,t}(0) \mid X_{i,t-1}, N_{i,t-1}]$ where $\mathbb{E}[y_{i,t}(1) \mid X_{i,t-1}, N_{i,t-1}]$ is the VAT that can be collected through firm i in period t if firm i is selected for monitoring. $\mathbb{E}[y_{i,t}(0) \mid X_{i,t-1}, N_{i,t-1}]$ is the VAT that can be collected through firm i in period t if firm i is not selected for monitoring. Under this approach, the government would estimate $\hat{r}_{i,t}$ for each firm and target those with the highest predicted causal effect. Thus, this policy objective would select the large taxpayers only if they have the highest predicted causal effect. I focus on the first policy objective in this paper because it is more aligned with the motivations of implementing a large taxpayer program. However, in future work, I aim to use audit outcomes and costs to study a revenue-optimal selection.

Finally, in Section 3.5, I estimate $\hat{y}_{i,t}$ with a random forest and analyze its predictive performance in comparison to two benchmark models: Lasso and Elastic Net. I assume that the Tax Agency does not disclose its selection procedure, and that taxpayers cannot recognize which model is used; thus, reporting behavior does not depend on the choice of model.

3.3 Data

The Ecuadorian Tax Agency periodically collects a large amount of data from the tax returns that can be used to characterize the taxpayers. I use four administrative datasets provided by the Tax Agency:

- Corporate income tax returns (*Formulario 101*)
- VAT returns (*Formulario 104*)
- Purchases annex (*Anexo Transaccional Simplificado, ATS*)
- Tax registry

Corporate Income Tax Returns *(Formulario 101)*. Firms report annual information from their balance sheets and income statements through the corporate income tax return. This information covers the fiscal year, which coincides with the calendar year, and it is filed in April of the following year. The tax returns reflect the annual operations of the firm and include: revenues, costs and expenses, assets and their components (e.g., current assets, long-term assets), liabilities and their components (e.g., short and long-term liabilities), equity.

VAT Returns *(Formulario 104)*. This source of information reflects the monthly economic activities of taxpayers. Firms report sales, purchases, sales subject to VAT, and purchases subject to VAT, output VAT (VAT received on sales to clients), input VAT (VAT paid on purchases of inputs and services), and VAT due (the difference between output VAT and input VAT).[5]

Purchases annex *(Anexo Transaccional Simplificado, ATS-Compras)*. The purchases annex is filed together with the VAT returns. This annex lists all purchases made by the taxpayer during the month, whether they are subject to VAT or not, the VAT of the transactions, any amounts withheld, and includes the tax ID of the supplier. It supports the claim of input VAT credits. This annex is a unique source of information on the economic activities of the reporting firm's suppliers.

Tax registry. This dataset contains information on the firm's characteristics that do not vary over time. The Tax Agency records information on the location of the firm (e.g., province, canton, city), the industry following a 6-digit ISIC standard classification from the United Nations, and the date of creation.

5. The Data Appendix of Chapter 2 presents a detailed description of the variables observed in the VAT returns.

3.3.1 Target variables in the prediction exercise

The goal of the Tax Authority is to identify the firms that are important for VAT collection. I consider two targets for prediction: the firm's own VAT liabilities and the VAT of its suppliers, which can be observed through the firm's purchase annex.

Firm's VAT liabilities. I use the annual average VAT due, defined as output VAT minus input VAT, to measure each firm's contribution to VAT collection. This measure reflects the net tax generated due to the firm's current economic activity. Alternative measures, such as the balance to be paid, are affected by withholding and the use of tax credits accumulated in previous periods. These factors make the balance to be paid less comparable across firms as a measure of their contribution to VAT collection.

VAT observed through the firm. The selection of special taxpayers not only targets the behavior of the firm itself but also that of its trade partners. First, special taxpayers collect VAT of the suppliers via withholding, and second, the government aims to increase the suppliers' perception of a future audit. To capture both objectives, I use the VAT associated with the purchases from non-special taxpayer suppliers as a second target variable in the prediction exercise. I exclude purchases from suppliers that are themselves special taxpayers, as they are already subject to monitoring and therefore not relevant to shifts in perceptions of audits. I use the annual average as the target measure.

3.3.2 Predictors

As mentioned before, the Tax Agency collects a large volume of information on firms through different tax forms. Even though this information is rich, many variables capture similar aspects of firm behavior, for example, revenues reported in the corporate income tax return and sales reported in the VAT return. To avoid redundancy, I select predictors that contribute relevant and different information for predicting the target variables. Table 3.1 presents the selected variables used in the prediction exercise and the tax forms from which they are obtained. Table 3.B.1 presents descriptive statistics.

3.3.3 Sample Construction

I first use information from 2013 to select predictors, since this is the earliest year for which data are available. I construct target variables for 2014 and train different models using the 2013 predictors and 2014 outcomes. The goal of the exercise is to assess whether the government can predict outcomes in year t using information available in year $t-1$. After selecting the model with the best performance, I test it using 2014 predictors and compare its predictions with the 2015 outcomes.

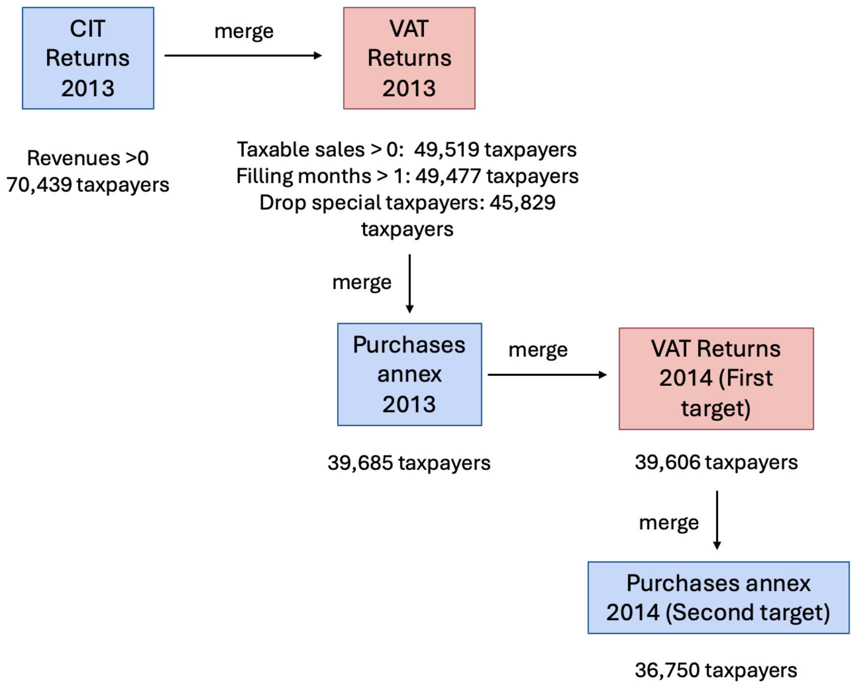
Table 3.1. Predictors

Group	Predictors	Source	Tax form
Stock variables	Assets	CIT returns	Formulario 101
	Liabilities	CIT returns	Formulario 101
	Accounts payable	CIT returns	Formulario 101
	Accounts receivable	CIT returns	Formulario 101
Flow variables	Income of the exercise (USD and probability of reporting a positive value)	CIT returns	Formulario 101
	Taxable sales (subject to VAT)	VAT returns	Formulario 104
	Coefficient of variation of taxable sales	VAT returns	Formulario 104
	Taxable purchases (subject to VAT)	VAT returns	Formulario 104
	Months filling VAT returns	VAT returns	Formulario 104
Characteristics	Dummies by province	Tax registry	
	Dummies by industry	Tax registry	
	Age	Tax registry	
Network characteristics	Total number of suppliers	Purchases annex	ATS - Compras
	Total number of suppliers that are individually-owned firms (share of total suppliers)	Purchases annex	ATS - Compras
	Total number of suppliers that are corporate firms (share of total suppliers)	Purchases annex	ATS - Compras
	Total number of suppliers that are special taxpayers (share of total suppliers)	Purchases annex	ATS - Compras
	Total number of suppliers in the service sector	Purchases annex	ATS - Compras
	Total number of suppliers in the retail sector	Purchases annex	ATS - Compras
	Total number of suppliers in the manufacturing sector	Purchases annex	ATS - Compras
	Total number of suppliers in the other industries	Purchases annex	ATS - Compras
	Number of industries covered by suppliers	Purchases annex	ATS - Compras
	Number of provinces covered by suppliers	Purchases annex	ATS - Compras

Notes: The table lists the variables used for predicting VAT due of the firm and VAT collected through the firm. Stock variables refer to end-of-year balances, whereas flow variables are yearly averages. Network characteristics are constructed from the purchases reported in the ATS and capture supplier composition, industry, and geographic reach. Return to the main text.

The construction of the sample for the prediction exercise starts with the corporate income tax returns from 2013. I restrict the sample to taxpayers that reported positive revenues, which I interpret as an indication that the firm was active during the year. This restriction results in a sample of 70,439 firms. Next, I merge this sample with VAT returns and keep the observations with information in both tax forms. I then drop observations that report zero taxable sales, as they will not report a VAT due (first target). I also exclude firms that only report the VAT return in one month of the year, firms already classified as special taxpayers in 2013 and 2014, and firms that do not report information on the purchases annex (network information). After accounting for these restrictions, I have a dataset with 39,606 observations with complete information for the first target and 36,750 observations with complete information for the second target. Figure 3.1 describes the sample construction in detail.

Figure 3.1. Sample Construction



Notes: This diagram shows the datasets that were merged, the restrictions applied at each step, and the number of taxpayers kept after each restriction. Return to the main text.

3.4 Empirical Strategy

I use three models to predict the VAT due of the firm and the VAT that can be observed through the firm: Lasso, Elastic Net, and Random Forest. Lasso and

Elastic Net are used as benchmarks that represent simpler models (Hastie et al., 2009; Zou and Hastie, 2005), while Random Forest is evaluated relative to these benchmarks. I also compare the performance of the three models against predicting the average VAT due (or the average VAT that can be observed through the firm) for all observations.

Lasso Model

The Lasso (*Least Absolute Shrinkage and Selection Operator*) improves prediction accuracy by shrinking the coefficients of unimportant variables, and in some cases, it sets some of them exactly to zero (Tibshirani, 1996). Due to this characteristic, the model performs variable selection and keeps the most informative predictors.

Hastie et al. (2009) define the Lasso problem as follows:

$$\hat{\beta}^{\text{lasso}} = \arg\min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{3.3}$$

Where p is the number of features (predictors) and n is the number of observations. The first term of the Lasso problem is a minimization of the sum of squared residuals, while the second term ($\lambda \sum_{j=1}^{p} |\beta_j|$) introduces a penalty on the absolute value of the coefficients. $\lambda > 0$ is the regularization parameter that determines the level of this penalty. To select the value of λ, a cross-validation procedure can be implemented to find a value that minimizes the RMSE.

Elastic Net

The second benchmark model is Elastic Net. Zou and Hastie (2005) define the elastic net penalty in the following way:

$$\left(\alpha \sum_{j=1}^{p} |\beta_j| + (1-\alpha) \sum_{j=1}^{p} \beta_j^2 \right) \tag{3.4}$$

While the first term of the penalty tends to shrink coefficients towards zero (*Lasso penalty*), the second term encourages more balanced coefficient values when features are highly correlated (Hastie et al., 2009). α determines the weight of the two types of penalties. Elastic Net may outperform Lasso in settings where the predictors are highly correlated, which can be the case when working with tax data. Unlike Lasso, which tends to select only one variable from a group of correlated predictors, Elastic Net allows for the inclusion or exclusion of all the variables of the correlated group (Zou and Hastie, 2005).

The Elastic Net problem is defined in Equation 3.5:

$$\hat{\beta}^{\text{enet}} = \arg\min_{\beta} \left\{ \frac{1}{2} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \left(\alpha \sum_{j=1}^{p} |\beta_j| + (1-\alpha) \sum_{j=1}^{p} \beta_j^2 \right) \right\} \tag{3.5}$$

The penalty parameter λ and weight α are determined using cross-validation, as will be explained later.

Random Forest

The Random Forest Model, introduced by Breiman (2001), builds B decision trees, each trained on a bootstrapped sample of the data. At each split within a tree, the algorithm randomly selects m of the p available features, identifies the best variable and threshold to divide a node, and repeats the process on the resulting child nodes (Hastie et al., 2009). The final prediction is obtained by averaging the predictions of all trees. Regarding the selection of the best variable and threshold, the algorithm picks the combination with the largest reduction in variance of the target variable.

To illustrate how the algorithm works, Figure 3.A.1 shows an example of one decision tree from a Random Forest. The example considers a dataset with six features. At the first split, a random subset of three features is selected (e.g., $m = 3$), and the algorithm identifies the best variable and corresponding threshold to divide the node. This process creates two child nodes, and the same procedure is applied again in each of the new nodes. The predictions of the model are observed at the end of the leaves of the terminal nodes. An observation that reaches a leaf is assigned the corresponding prediction (e.g., e, f, g, h).

As described in Section 3.4.1, I use different values for the number of predictors that can be considered at each split (m). While the example in Figure 3.A.1 considers a tree with three levels, in my implementation, I require a minimum node size of five observations to grow a tree. This means that a split occurs if the child nodes have at least five observations.

3.4.1 Estimation using Machine Learning

I use nested cross-validation to assess the performance of the three models: Lasso, Elastic Net, and Random Forest. Nested cross-validation consists of two loops: the outer loop and the inner loop. I begin with the outer loop by splitting the data into five folds (groups). In each of the five folds, I set aside one fold, which is the outer test set, and use the remaining four folds (outer training set) to find the best combination of hyperparameters. Then, the tuning of hyperparameters is done in the inner loop.

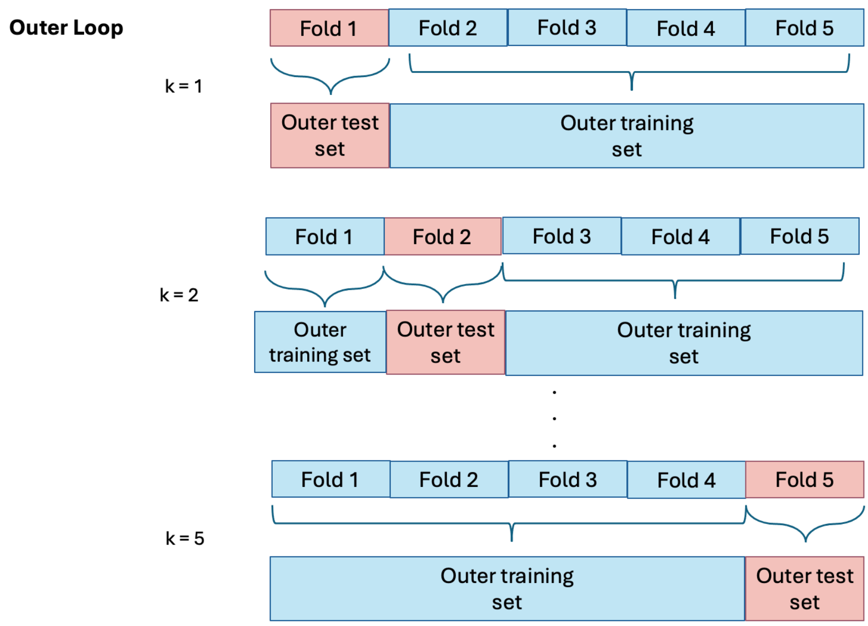
Within the inner loop, the outer training set is split again into five subsets: four folds are used for training, and one fold is used for validation of the trained model. This implies that each hyperparameter value (or combination of hyperparameters) is trained on the training data, and the validation data is used to compute predictions and the corresponding Root Mean Squared Error (RMSE). This results in five RMSE values per hyperparameter (or combination of hyperparameters), which I average to obtain a single RMSE. The hyperparameters with the lowest average RMSE are selected, and the model is retrained on the full outer training set. I then evaluate this trained model on the outer test fold. This means that I compute predictions and the RMSE using the outer test fold. Since this process is repeated across all five outer folds, the Random Forest, Lasso, and Elastic Net would each have five RMSEs. I average the five resulting RMSEs to have a reliable estimate of the model's out-of-sample performance. The model with the best performance is that with the lowest average RMSE. Figure 3.2 illustrates how nested cross-validation is implemented.

For the Lasso model, the relevant hyperparameter is λ. I train the model using a grid of 100 values, ranging from 0.001 to 1000, spaced evenly on a logarithmic scale. For the Elastic Net, λ and α are tuned. I use the same grid for λ as in the Lasso model. For α, I use a grid of 11 values from 0 to 1 in increments of 0.1. This results in a total of 1,100 combinations of λ and α that are considered. For the Random Forest model, I tune the number of predictors considered at each split, denoted by m. The default choice is $m = p/3$ (Hastie et al., 2009). I test three values: $p/6$, $p/3$, and $2p/3$.[6]

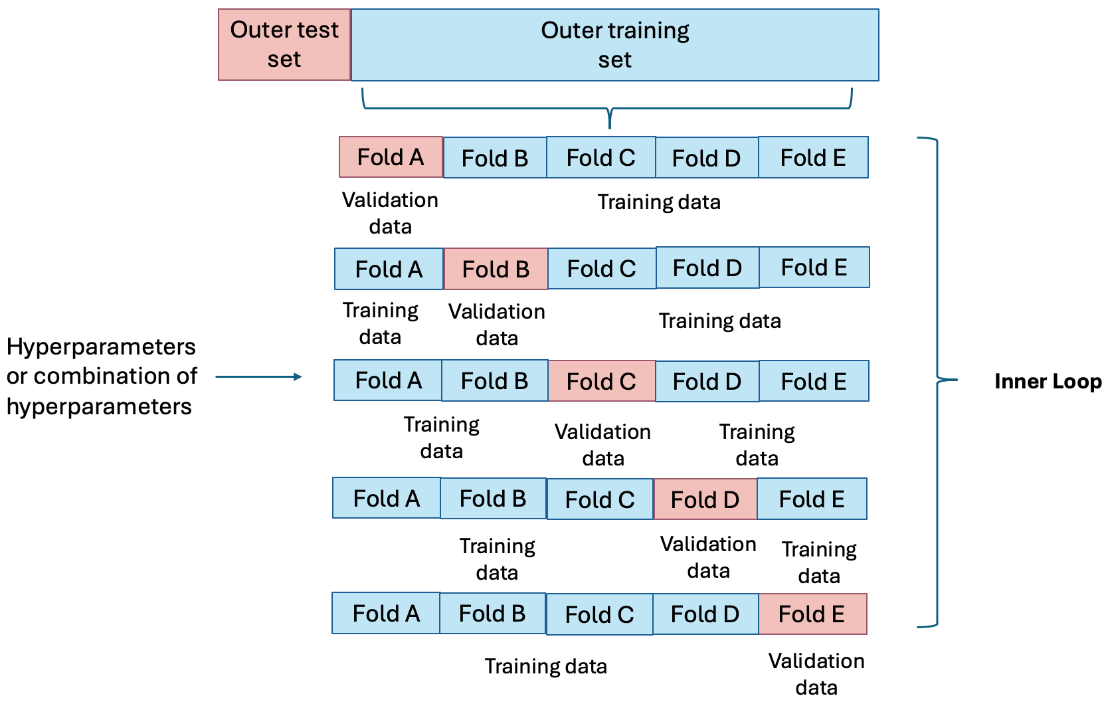
I compare the average RMSE of the Lasso, the Elastic Net, and the Random Forest Model computed using data from 2013 to predict 2014 outcomes. One should note that I use outcome variables (the firm's VAT liabilities and VAT observed through the firm) reported in tax administrative datasets, which may differ from true tax liabilities when tax evasion exists. Therefore, the exercise should be viewed as a second-best approach. However, as mentioned in Section 3.2, in future work, I aim to integrate audit information into the selection of special taxpayers.

6. The minimum number of observations required for a leaf node is set to the default value of 5, and the Random Forest grows 500 trees.

Figure 3.2. Nested cross-validation Example



(a) Outer Loop Example



(b) Inner Loop Example

Notes: This diagram shows how nested cross-validation is implemented. Panel (a) illustrates the outer loop while Panel (b) shows how the inner loop works for the first outer fold (k=1). Once the fold is divided into outer test set and outer training set, the latter is split one more time into five folds. Hyperparameters are trained using four folds (sky blue folds), and the predictions and RMSE are computed using the validation data (orange fold). The hyperparameters with the lowest RMSE are used to refit the training data. After that, the model performance is evaluated using the outer test fold. Return to the main text.

3.5 Results

3.5.1 Predicting VAT liabilities

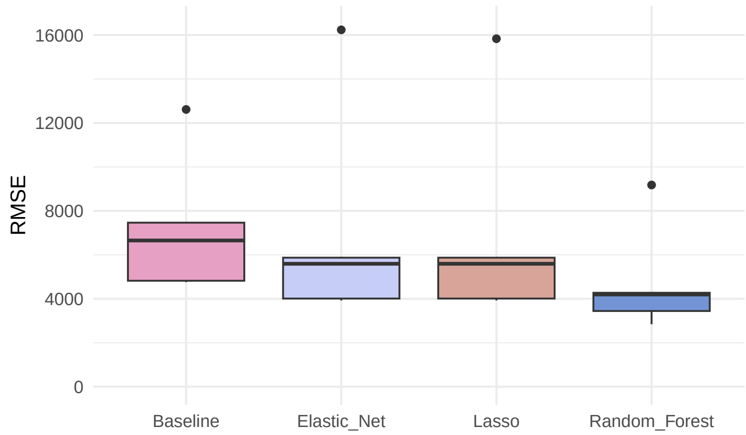
I use the RMSE to evaluate the performance of the Random Forest model and compare it with three benchmarks: the Lasso RMSE, the Elastic Net RMSE, and a Baseline RMSE. The Baseline RMSE is computed by predicting the mean of the VAT due in the training data for all observations in the outer-test data and can be considered a naive prediction model. This benchmark ignores all predictors when forecasting. One can argue that a model that does not outperform this baseline adds no predictive value beyond simply using the sample average.

Figures 3.3 and 3.4 show the distribution of RMSE values for the Random Forest and the three benchmarks across the five outer folds of the nested cross-validation. Figure 3.3 corresponds to a prediction exercise that excludes network characteristics (Exercise 1), while Figure 3.4 corresponds to a prediction exercise, which includes all predictors (Exercise 2).[7]

The Random Forest outperforms the other models in both prediction exercises. It presents the lowest average RMSE and the lowest variability across the five outer folds (Table 3.B.2). As expected, the baseline model, which predicts the training mean, has the highest average RMSE and a wider spread of values. The Elastic Net and Lasso Models have a similar performance. This is because the grid i the Elastic Net includes a value of $\alpha = 1$, and in inner loops, the selected α is 1, which reduces the Elastic Net to a Lasso Model. It is also important to mention that one of the outer folds produced a high RMSE across all models, which are represented as black circles in the boxplot, and suggests that model performance can decline in the presence of large variation in the sample composition. Overall, Random Forest has the best predictive performance, and thus, including nonlinear interactions among predictors improves the accuracy of VAT due predictions. However, its improvement over the baseline (e.g., predicting the mean VAT liabilities from the training data in each outer fold) is modest, with an RMSE reduction of only 35%.[8]

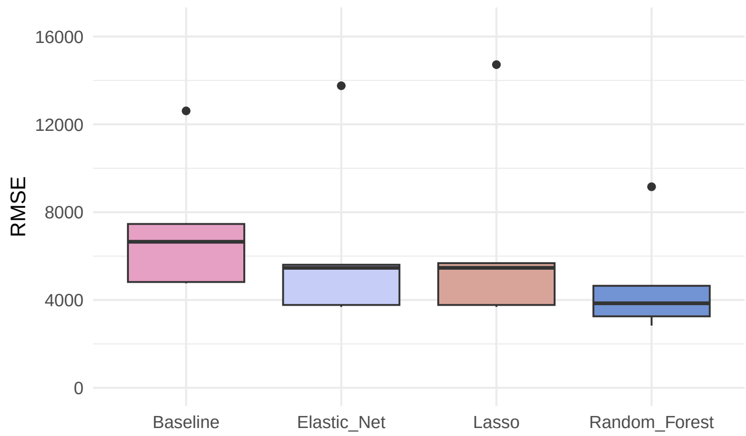
7. Exercise 1 uses 57 predictors while Exercise 2 uses 73 predictors.
8. The improvement is calculated as $\frac{\text{Random Forest RMSE - Baseline RMSE}}{\text{Baseline RMSE}}$

Figure 3.3. Performance of Exercise 1



Notes: This figure summarizes the distribution of RMSE values for the Elastic Net, Lasso, and Random Forest models, based on five outer folds of nested cross-validation. A baseline RMSE, computed using the mean outcome of the training set, is also included for comparison. Exercise 1 predicts VAT due, excluding network characteristics as predictors. Return to the main text.

Figure 3.4. Performance of Exercise 2



Notes: This figure summarizes the distribution of RMSE values for the Elastic Net, Lasso, and Random Forest models, based on five outer folds of nested cross-validation. A baseline RMSE, computed using the mean outcome of the training set, is also included for comparison. Exercise 2 predicts VAT due, including network characteristics as predictors. Return to the main text.

The performance of the model does not change significantly when network characteristics are included as predictors (Table 3.B.3). To assess variable importance, I use an impurity-based importance ranking, which measures the contribution of each variable to reducing the residual sum of squares across all trees in the Random Forest. Figures 3.A.2 and 3.A.3 show the most important predictors for models with and without network characteristics, respectively. Taxable sales, taxable purchases, and assets are the most important predictors in both specifications; however, when network characteristics are included, some of these also become important, such as the number of industries covered by suppliers or the taxable sales per special taxpayer.

In the prediction exercises, I use the default value for the minimum number of observations required in a leaf node (*min node size*). To assess whether performance improves with alternative values, I implement nested cross-validation with a grid of three values for min node size: 5 (the default), 15, and 20, and the same grid for m. Table 3.B.6 reports the results. The performance of the Random Forest model when *min node size* is tuned is similar to that of Exercise 2. Due to the computational cost, the following exercises only consider m as the hyperparameter to be tuned.

3.5.2 Predicting VAT observed through the firm

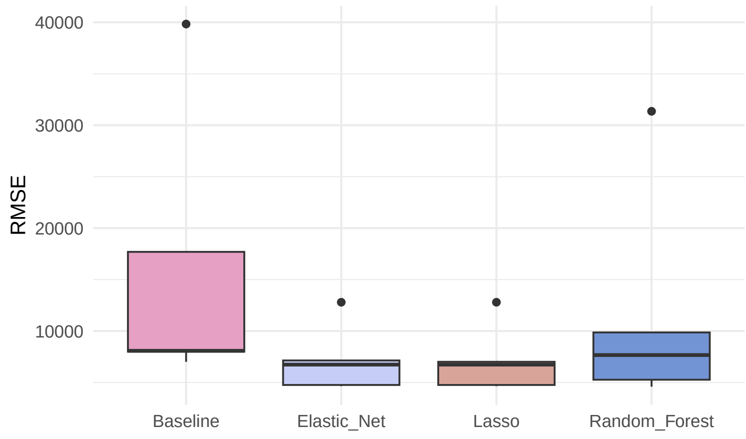
I now turn to the prediction of the second target: the VAT observed through the firm or the input VAT in purchases with non-monitored suppliers. Exercise 3 excludes network characteristics (Figure 3.5), while Exercise 4 incorporates them (Figure 3.6).[9]

As in the previous analysis, the figures show the distribution of RMSE values across five outer folds for Baseline, Lasso, Elastic Net, and Random Forest models. In both specifications, Lasso and Elastic Net outperform Random Forest, achieving a lower mean RMSE and more stable performance across folds. This indicates that the Random Forest model may not be a good alternative for predicting the input VAT of non-monitored suppliers.

Comparing the results of the two exercises (Table 3.B.4 and Table 3.B.5), I find that including network characteristics does not affect the ranking of models but does slightly reduce the average RMSE for Lasso and Elastic Net. This finding may indicate that some network variables have a small contribution to the prediction.

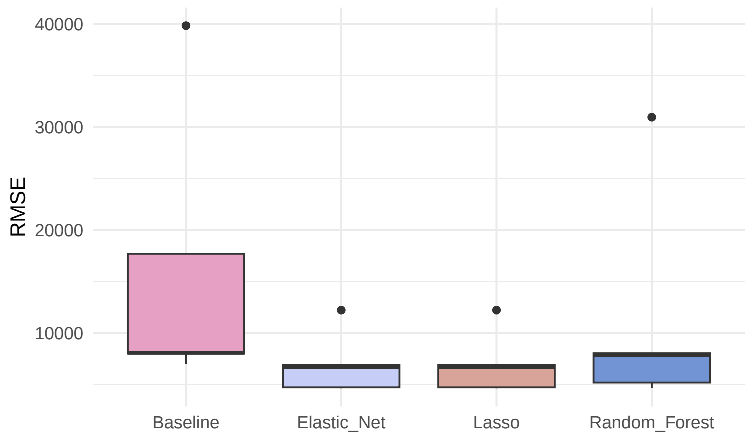
9. Exercise 3 has 57 predictors and Exercise 4 includes 73 predictors.

Figure 3.5. Performance of Exercise 3



Notes: This figure summarizes the distribution of RMSE values for the Elastic Net, Lasso, and Random Forest models, based on five outer folds of nested cross-validation. A baseline RMSE, computed using the mean outcome of the training set, is also included for comparison. Exercise 3 predicts the input VAT of unmonitored suppliers, excluding network characteristics as predictors. Return to the main text.

Figure 3.6. Performance of Exercise 4



Notes: This figure summarizes the distribution of RMSE values for the Elastic Net, Lasso, and Random Forest models, based on five outer folds of nested cross-validation. A baseline RMSE, computed using the mean outcome of the training set, is also included for comparison. Exercise 4 predicts the input VAT of unmonitored suppliers, including network characteristics as predictors. Return to the main text.

3.5.3 Assessing the performance of the Random Forest Model

Since the Random Forest Model performs better than the other models for predicting firms' VAT liabilities (VAT due), the next exercises use this outcome as the target variable.

The nested cross-validation implemented in Section 3.5.1 is designed to provide a good estimate of out-of-sample performance; however, it relies on data from a single combination of years. Therefore, I conduct an additional robustness check to assess whether the model can be used on a different combination of years. I perform a fivefold cross-validation on the dataset used in Exercise 2 to determine the best value for m and refit the model on the entire dataset.[10] Then, I use this trained model to predict the 2015 VAT due using predictors from 2014. The goal of this exercise is to examine whether the model has learned generalizable patterns or if its performance depends on specific characteristics of a year.

Table 3.2 presents performance indicators of the Random Forest. The RMSE is 9,548, but the improvement over the Baseline RMSE falls to 28%, compared to 35% in the original implementation. The corresponding R^2 is 0.49, which suggests that the model explains 49% of the variation in VAT due. Even though the predictions obtained from the Random Forest model are better than the naive predictions based on the mean of the VAT due, the modest improvement suggests that there is room to refine the prediction model before using it for the selection of special taxpayers.

Table 3.2. Performance of Random Forest (2014 predictors and 2015 targets)

Indicator	Value
RF RMSE	9,548
Baseline RMSE	13,344
Improvement	28%
R^2	0.49

Notes: The table reports performance indicators for Model 2, which was first trained using 2013 predictors and the 2014 VAT due and then used in a new dataset that combines 2014 predictors and the 2015 VAT due as the target.

As a final exercise, I trained prediction models using features from 2013 and 2014, and the corresponding average VAT liabilities for 2014 and 2015 (Exercise 5).[11] I use nested cross-validation to assess whether the performance of a Random

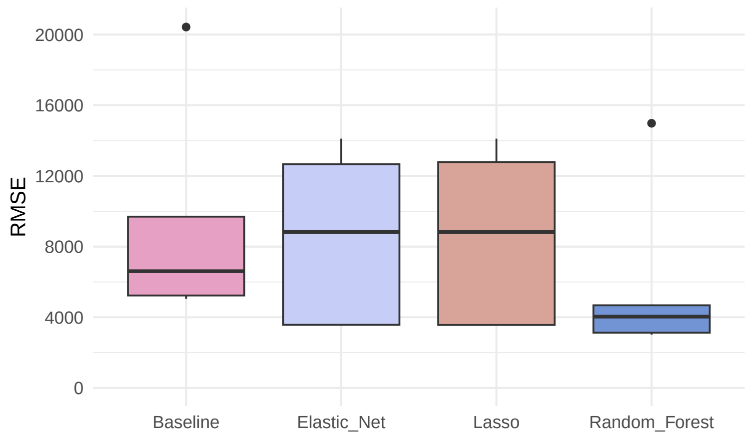
10. The best value of m is 48, thus 48 predictors are considered to determine the best combination of variable and threshold at each split.

11. I did not use information from 2016 since Ecuador had an earthquake that year, which affected two provinces and represents an exceptional event.

Forest model is better than that of Lasso and Elastic Net, and I use the trained model on a new dataset with 2017 predictors and 2018 VAT liabilities. I rank firms based on their predicted VAT liabilities and analyze which firms would have been selected based on these predictions.

Figure 3.7 presents the results of the performance of the different forecasting models using nested cross-validation. The Random Forest once again has the best performance, with the lowest average RMSE (Table 3.B.7). However, it performs worse than the Lasso and Elastic Net Models in the first fold. The Random Forest may not outperform linear models in all cases, and its performance may vary depending on the composition of the data.

Figure 3.7. Performance of Exercise 5



Notes: This figure summarizes the distribution of RMSE values for the Elastic Net, Lasso, and Random Forest models, based on five outer folds of nested cross-validation. A baseline RMSE, computed using the mean outcome, is also included for comparison. Exercise 5 predicts the VAT due using information between 2013 and 2015. Return to the main text.

Next, I perform a fivefold cross-validation on the data used in Exercise 5 to choose hyperparameters and refit the model on the entire dataset. This trained model is used to compute predictions on the 2017-2018 dataset.[12]

Since the government's objective is to select the most important firms within each province, I compute two provincial rankings: one based on the actual VAT liabilities in 2018 and one based on the predicted VAT liabilities. I then use the actual number of firms selected in each province and assess whether a selection rule based on predicted VAT liabilities would correctly identify the top firms. To evaluate this, I compute a measure of *recall* for each province defined as follows:

12. The tuning after fivefold cross-validation results on $m = 12$.

$$recall = \frac{TP}{(TP + FN)} \tag{3.6}$$

where TP (True Positives) refers to the number of firms that are ranked among the top in a province based on predicted VAT liabilities, and also belong to the top group based on actual VAT liabilities reported in 2018. FN (False Negatives) refers to the number of firms that are not ranked among the top in a province based on predicted VAT liabilities but do belong to the top group based on actual VAT. For comparison purposes, I also compute a measure of recall using the actual selection made by the Tax Agency.

Table 3.3 presents the recall scores for the two selections. The average recall of the selection based on the predicted VAT liabilities is 0.57, indicating that more than half of the top firms are correctly identified. In contrast, the average recall of the actual selection made by the Tax Agency is 0.29. However, the Tax Agency may consider additional objectives or constraints that are not disclosed.

One limitation of this final exercise is that the 2018 VAT liabilities used to construct the benchmark rankings include firms that were selected as special taxpayers in 2018. Thus, the observed VAT liabilities reflect a treatment effect associated with the selection. Nevertheless, even with this limitation, using the VAT liabilities that include the treatment effect to compute the benchmark rankings remains reasonable, as the relative ranking of firms should not change substantially.

Table 3.3. Recall by province

Province	# Firms selected by province	Recall using the predicted VAT	Recall Selection of the Tax Agency
El Oro	22	0.68	0.23
Esmeraldas	6	0.33	0.33
Guayas	215	0.59	0.33
Los Ríos	5	0.60	0.20
Manabí	17	0.47	0.18
Santa Elena	3	0.67	0.33
Azuay	26	0.69	0.35
Cañar	1	0	0
Carchi	2	0.50	0
Cotopaxi	5	0.60	0
Chimborazo	4	0.75	0.50
Imbabura	15	0.60	0.33
Loja	5	0.40	0
Pichincha	220	0.60	0.34
Tungurahua	8	0.50	0.13
Santo Domingo	11	0.55	0.36
Pastaza	1	1	1
Zamora Chinchipe	1	1	1
Sucumbíos	1	1	0
Orellana	2	0.50	0
Galápagos	2	0	0.50
Average recall		0.57	0.29

Notes: The table presents the recall of a selection based on the predicted average VAT due and the recall of the actual selection made by the Tax Agency. Return to the main text.

3.6 Discussion and Conclusions

In this paper, I discuss the selection of large taxpayers for tax monitoring using machine learning methods. I focus on the special taxpayer program in Ecuador and, considering the program's goal, define two targets for prediction exercises: the value-added tax reported by each firm and the value-added tax of the firm's suppliers, which is observed through the transactions reported by the firm. I compare the performance of Random Forest Models with respect to that of Lasso and Elastic Net Models, and analyze how the Random Forest Model can be used to rank firms based on predicted VAT liabilities.

I find that the Random Forest Model performs better in forecasting the first goal (the value-added tax reported by each firm) than in forecasting the second goal (the value-added tax observed through the firm); however, there are some limitations to generalizing a model trained in some years to a different combination of years. Further, when ranking firms based on predicted VAT liabilities in 2018, I find that 57% of the firms are correctly ranked. This evidence indicates that there is still room for improvement in the forecasting models before using them to select special taxpayers.

This paper explores one application of machine learning: the selection of firms into large taxpayer programs based on predicted VAT liabilities. Machine learning can be used in other ways to support the selection of firms. The Tax Agency can predict firms' tax non-compliance and use the predictions to identify high-risk firms. Then, they can target large firms connected to suppliers likely to misreport. Another strategy could be to adopt a two-stage approach in which firms are first screened using size-based criteria and then ranked using machine learning estimates of treatment effects. This would allow the administration to prioritize firms expected to generate the largest compliance or revenue gains if included in the program. Future research, in collaboration with the Tax Agency, could help assess the performance of these two strategies.

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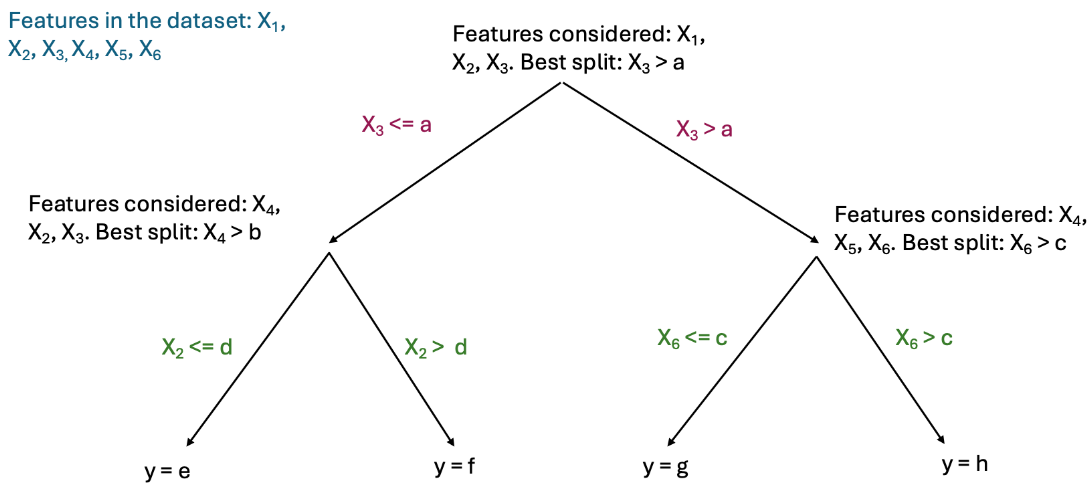
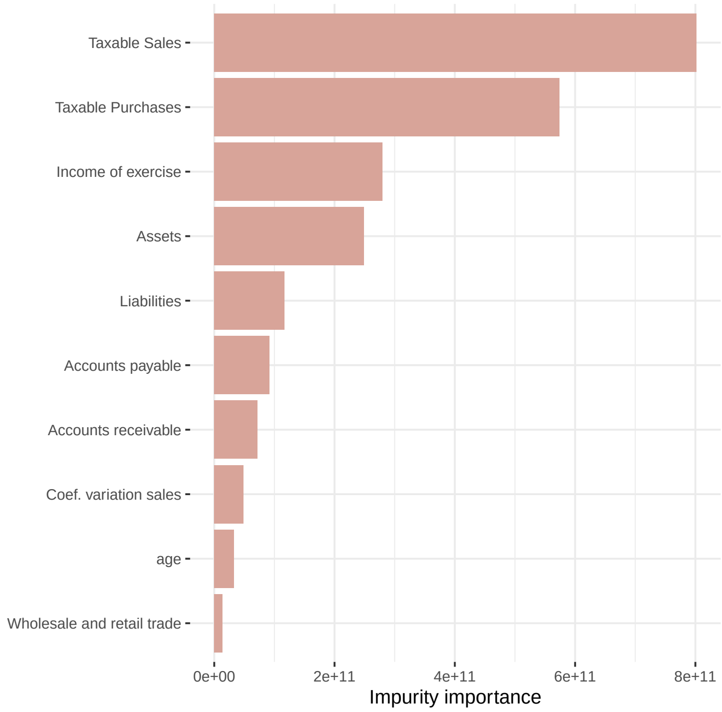
3.A Additional Figures

Figure 3.A.1. Example of a Decision Tree in a Random Forest



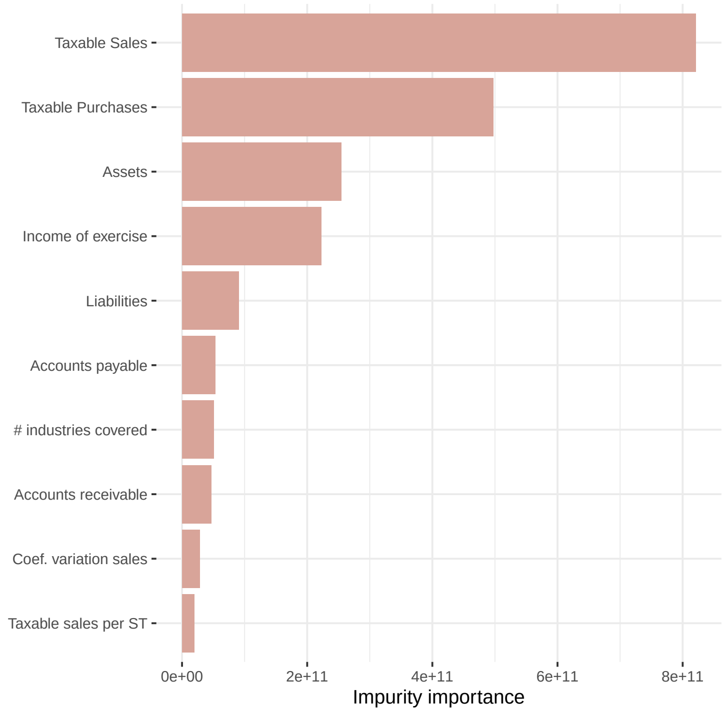
Notes: This diagram presents a simple representation of a decision tree in a Random Forest. The example considers a dataset with 6 features. At each split, a random subset of 3 features is selected, and the algorithm decides which is the best variable and threshold to do the split. The letters e, f, g, and h represent the predicted values assigned to an observation that reaches the corresponding leaf of the tree. Return to the main text.

Figure 3.A.2. Most important predictors in Exercise 1



Notes: This figure shows the most important predictors in Model 1, based on impurity importance. The impurity importance score reflects how much each variable contributes to reducing the residual sum of squares across all trees in the Random Forest. Model 1 predicts VAT due, excluding network characteristics as predictors. Return to the main text.

Figure 3.A.3. Most important predictors in Exercise 2



Notes: This figure shows the most important predictors in Model 2, based on impurity importance. The impurity importance score reflects how much each variable contributes to reducing the residual sum of squares across all trees in the Random Forest. Model 2 predicts VAT due, including network characteristics as predictors. Return to the main text.

3.B Additional Tables

Table 3.B.1. Summary Statistics

Variable	Mean	SD	Variable	Mean	SD
VAT due	2016.24	7809.35	VAT collected through the firm	2.91	20.39
Taxable sales	37.97	240.23	Taxable purchases	29.02	234.51
Months filling VAT	11.70	1.33	Coefficient of Δ taxable sales	119.11	98.95
Assets	622.72	5602.40	Liabilities	373.71	2284.63
Income of the exercise	44.38	1126.16	Accounts receivable	154.82	1620.95
Accounts payable	172.73	1156.90	Prob (income of exercise >0)	0.73	0.45
Age (year)	8.86	8.38	Total number of suppliers	19.43	24.26
Number of suppliers that are individually-owned firms	8.49	12.39	Number of suppliers that are corporate firms	4.58	6.13
Number of suppliers that are special taxpayers	6.08	7.28	Number of industries covered	5.2	3.31
Number of provinces covered	2.52	1.64			

Notes: Variables are in USD thousands unless otherwise indicated. Coefficient of Δ taxable sales is computed as the standard deviation of taxable sales divided by the mean taxable sales times 100. Return to the main text.

Table 3.B.2. Performance of Exercise 1

Outer Folds	Baseline RMSE	Lasso RMSE	Elastic Net RMSE	Random Forest RMSE
1	6,653	5,593	5,593	4,273
2	12,614	15,833	16,236	9,178
3	7,463	5,870	5,870	4,196
4	4,759	3,924	3,924	2,874
5	4,820	4,010	4,010	3,444
Average RMSE	7,262	7,046	7,127	4,787
SD RMSE	3,213	4,991	5,169	2,523

Notes: The table presents the RMSE corresponding to each method and for every outer fold. The models predict VAT due in 2014 using predictors of 2013. The last two rows present the average and standard deviation of the RMSE. The Average RMSE of Random Forest is highlighted in blue to indicate that it is the model with the lowest RMSE. Return to the main text.

Table 3.B.3. Performance of Exercise 2

Outer Folds	Baseline RMSE	Lasso RMSE	Elastic Net RMSE	Random Forest RMSE
1	6,653	5,465	5,465	3,850
2	12,614	14,721	13,758	9,158
3	7,463	5,678	5,606	4,645
4	4,759	3,685	3,685	2,835
5	4,820	3,773	3,773	3,256
Average RMSE	7,262	6,664	6,458	4,749
SD RMSE	3,213	4,597	4,180	2,557

Notes: The table presents the RMSE corresponding to each model and for every outer fold. The models predict VAT due in 2014 using predictors of 2013 (including information about networks). The last two rows present the average and standard deviation of the RMSE. The Average RMSE of Random Forest is highlighted in blue to indicate that it is the model with the lowest RMSE. Return to the main text.

Table 3.B.4. Performance of Exercise 3

Outer Folds	Baseline RMSE	Lasso RMSE	Elastic Net RMSE	Random Forest RMSE
1	17,694	6,736	6,736	7,664
2	39,834	12,796	12,796	31,353
3	7,993	4,640	4,640	5,267
4	7,009	4,757	4,757	4,589
5	8,079	7,009	7,141	9,863
Average RMSE	16,122	7,188	7,214	11,747
SD RMSE	13,951	3,320	3,313	11,156

Notes: The table presents the RMSE corresponding to each model and for every outer fold. The model predicts the input VAT of suppliers that are not special taxpayers in 2014 using predictors from 2013. The last two rows present the average and standard deviation of the RMSE. The RMSE of the Lasso Model is highlighted in blue to show that it is the model with the best performance. Return to the main text.

Table 3.B.5. Performance of Exercise 4

Outer Folds	Baseline RMSE	Lasso RMSE	Elastic Net RMSE	Random Forest RMSE
1	17,694	6,694	6,694	7,842
2	39,834	12,217	12,217	30,950
3	7,993	4,623	4,623	5,185
4	7,009	4,717	4,717	4,654
5	8,079	6,900	6,900	9,303
Average RMSE	16,122	7,030	7,030	11,332
SD RMSE	13,951	3,089	3,089	11,072

Notes: The table presents the RMSE corresponding to each model and for every outer fold. The model predicts the input VAT of suppliers that are not special taxpayers in 2014 using predictors from 2013. The last two rows present the average and standard deviation of the RMSE. Return to the main text.

Table 3.B.6. Tuning the minimum node size

Outer Folds	Number of predictors considered at each split (m)	Minimum node size	RMSE	RMSE (Exercise 2)
1	12	5	3,960	3,850
2	48	15	9,362	9,158
3	12	5	4,564	4,645
4	12	5	2,826	2,835
5	48	5	3,300	3,256
		Average RMSE	4,802	4,749

Notes: The table presents the RMSE corresponding to a Random Forest Model where the minimum node size is tuned (Column 3) and the RMSE of the Random Forest Model in Exercise 2. Return to the main text.

Table 3.B.7. Performance of Exercise 5

Outer Folds	Baseline RMSE	Lasso RMSE	Elastic Net RMSE	Random Forest RMSE
1	20,424	14,110	14,110	14,979
2	5,233	3,566	3,574	3,130
3	5,047	3,556	3,548	3,021
4	9,695	12,780	12,658	4,038
5	6,606	8,828	8,828	4,678
Average RMSE	9,401	8,568	8,544	5,969
SD RMSE	6,437	4,967	4,941	5,083

Notes: The table presents the RMSE corresponding to each model and for every outer fold. I merge two datasets that combine predictors in 2013 and VAT due in 2014, and predictors in 2014 and VAT due in 2015. The last two rows present the average and standard deviation of the RMSE. The Average RMSE of Random Forest is highlighted in blue to indicate that it is the model with the lowest RMSE. Return to the main text.

Declaration

This dissertation is the result of my own work, and no other sources or means, except the ones listed, have been employed.

Mannheim, September 2025

Tania Guerra Rosero

Curriculum Vitae

2019–2025	**University of Mannheim** Ph.D. in Economics
2016–2017	**Barcelona Graduate School of Economics** M.Sc. in Specialized Economic Analysis - Economics of Public Policy
2012–2013	**Lund University** M.Sc. in Economic Development and Growth (double degree)
2011–2012	**Carlos III University** M.Sc. in Economic Development and Growth (double degree)
2005–2009	**Pontifical Catholic University of Ecuador** B.Sc. in Economics