Do Accountants Influence Their Client's Behavior? Evidence From an Imperfect Tax Withholding Regime

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Abstract

We use rich administrative data on turnover tax filings from Argentina and focus on the features of the withholding regime set up to collect the tax. We document sharp bunching exactly at the point where the withheld amount remitted by third-parties is equal to the tax liability declared by the firm and argue that this pattern is due to under-reporting of tax declarations incentivized by the withholding regime. By linking firms to tax accountants through shared contact information we are able to study whether they might be responsible for this behavior. First, we analyze how correlated are the behaviors of firms who share the same accountant. We are able to establish that there is a positive correlation between accountants and the bunching behavior observed on their clients. Second, we test whether there is a causal effect of accountants on firms by exploiting information on audits. We find that non-audited firms respond to their peer's audit, suggesting that accountants act as diffusers of information across clients.

1 Introduction

Withholding is a popular tax collection tool across the world. In developed countries it is common for employers to withhold income tax on behalf of their employees and transfer it directly to the government. Developing economies are increasingly relying on this mechanism by extending its use to other types of transactions such as sales taxes. Withholding generates a source of third-party information that may act as an evasion deterrent by leading taxpayers to increase their declarations in a way that is in line with what third-parties have reported (Kleven, Knudsen, et al., 2011; Pomeranz, 2015). On the other hand,

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the information that is generated may not translate to an increase in compliance if taxpayers can make offsetting adjustments on other margins of their tax declarations where information is harder to verify (Carrillo, Pomeranz, et al., 2017; Slemrod et al., 2017). This second alternative may actually be of most importance in developing countries where the majority of payments is still made in cash and businesses keep poor records of their transactions.

The literature analyzing behavioral responses to the tax system usually focuses on the taxpayers' reaction to changes in the tax regime. But, in many instances, it is overlooked that professional accountants are the ones mediating such responses. While individuals may not be fully informed about the tax regime's incentives, a hired professional can provide more sophisticated knowledge on how the tax system works and influence how the taxpayer responds (Chetty and Saez, 2013). Accountants may be playing an important role in the context of withholding by making its incentives more salient to their clients. Additionally, their frequent contact with multiple clients may be the link that enables relevant information to diffuse across taxpayers (Chetty, Friedman, and Saez, 2013; Battaglini et al., 2019; Boning et al., 2018). The main impediment to studying this issue has been that the relation between accountants and their clients is usually private information, barring researchers from knowing which professionals are interacting with which taxpayers.

In this paper, we study the withholding regime set up to collect monthly turnover tax filings in the province of Buenos Aires, Argentina. There, firms act as withholding agents by collecting part of the tax and transferring it directly to the government. We use administrative tax records for the 2017 fiscal year to analyze its effects on firm's reporting decisions. We document sharp bunching exactly at the point where the amount withheld by third-parties is equal to the firm's tax declaration and argue that this may constitute evidence of a behavioral response due to the incentives to under-report gross revenue that the withholding regime creates on firms. We then link firms to tax accountants through shared contact information and explore the possibility that they might be driving this response. We do this in two ways. First, by analyzing the correlation in bunching between clients of the same accountant. We find that there is a positive correlation of accountants on their client's bunching. Nevertheless, this may be purely driven by endogenous sorting of firms to accountants. To provide evidence of a causal effect, our second strategy implements an event-study research design that exploits monthly data on audits. Our goal is to test whether non-audited firms that share the same accountant with audited ones indirectly respond to the audit treatment. We find that non-audited firms react by increasing their tax filings after the audit, these coordinated responses can be attributed to the role of accountants diffusing information across clients.

The data are provided by the tax authority of the Province of Buenos Aires (ARBA: *Agencia Recaudadora de la provincia de Buenos Aires*). We look at monthly filings of the turnover tax for 2017. This tax is levied on approximately 1.3 million self-employed individuals and firms (for simplicity, we will refer to all taxpayers as firms) for whom we know their monthly declaration, the tax rate that was applied and if there existed any withheld amounts remitted by third-parties. For our empirical analysis we will focus on firms whose main activity is at the retail level (specifically: retail sales, hotel and restaurant services, and transportation). These firms constitute an ideal group to analyze the withholding system's incentives because most of their sales are made to final consumers where truthful reporting is harder to enforce, making it more likely for firms to evade the tax.

For each firm we also have individual characteristics such as industry classification, location, and contact information, enabling us to precisely relate different firms through shared email addresses to an accountant managing their taxes. Another set of records from ARBA provide us information on monthly audit procedures initiated throughout 2017. The high frequency of the data allows us to have multiple observations for each taxpayer in a short interval of time, a feature that we will exploit when we analyze the response to audits.

We begin by showing graphical evidence of a noticeable clustering of monthly tax filings precisely at the point where the amount withheld by third-parties is equal to the firm's reported tax declaration (we define this point as the "withholding threshold"). We suspect that at least part of this clustering is attributable to firms that are truly liable for a larger amount of tax but have decided to declare they owe exactly the amount that is reported by third-parties. We also show that firms locate at that point only sporadically through the year, consistent with the possibility that firms are manipulating their tax declarations only on specific circumstances. Then we try to answer whether these responses are driven by their tax accountants. We first estimate the correlation in bunching across clients from the same accountant and find a positive effect. We also show that this effect is larger in magnitude than the correlation in bunching for firms in the same industry or location. Taken together, these results suggest that accountants matter for explaining the tax-filing behavior of firms. Finally, we proceed to determine whether there exists a causal effect of accountants on their clients by looking at the effect that audits targeted to one firm have on their peer's behavior. We implement an event-study research design that allows us to measure the responses of targeted and non-targeted firms and find that firms that are not audited react very similarly to those that are. This result might be explained by accountants diffusing information across clients.

Our study contributes to two strands of literature. First, it contributes to the large body of work analyzing tax compliance and enforcement. Starting from the Allingham and Sandmo (1972) benchmark model where taxpayers decide how much to evade based on the probability of being detected and punished by the government, recent developments such as Kleven, Kreiner, et al. (2016), Kleven, Knudsen, et al. (2011), and Pomeranz (2015) have shown that the government's tax collection capacity may be boosted by the availability of third-party information. Withholding regimes have gained attention within this literature for being both a tool that enables governments to simplify enforcement while simultaneously generating third-party information on the transactions where it is applied (recent papers analyzing withholding in developing countries include: Brockmeyer and Hernandez, 2018; Carrillo and Shahe Emran, 2018; Waseem, 2018).

Our work is more in line with papers that highlight the potential limitations for the use of third-party information, such as Carrillo, Pomeranz, et al. (2017) and Slemrod et al. (2017). If firms can adjust other margins (where information is hard to verify for the tax authority), then the third-party information generated by withholding regimes will be deemed useless. We show that this is the case for firms filing turnover taxes in Buenos Aires. These firms make sales to final consumers, with few incentives to report all transactions. Then, it is possible that third-party withholding will only partially help raise taxes since firms will be able to under-report their sales up to the amount that has been withheld. This finding points out one potential limitation that governments might encounter when they design tax collection systems that rely on third-party information (in general) and withholding regimes (in particular), but at the same time suffer from information and enforcement constraints.

The second strand of literature we speak to is that related to the role of accountants. Some recent papers have highlighted the potential network effects for clients of the same tax professional. Boning et al. (2018) show that tax enforcement may have effects that extend beyond the targeted taxpayers due to linkages through a shared tax preparer. Battaglini et al. (2019) show that spillovers across clients are caused both by sorting of taxpayers into accountants and to the informational externalities generated by them. We are among the first to analyze the role of accountants in a developing country and to show suggestive evidence on how they act as information diffusers across clients. Given that tax evasion and avoidance are likely to be higher in the developing world, exploring one of the potential channels through which information on the tax regime might spread across taxpayers can have important policy implications for future advances on tax compliance and enforcement.

The remainder of the paper is organized as follows. In Section 2 we describe a simple framework that outlines the main features of tax-filing incentives under the withholding regime and explain the institutional context of the tax we study. In Section 3 we describe the data used for our analysis. In Section 4 we show graphical evidence of bunching and discuss its implications. In Section 5 we study the effects of accountants on their clients' tax-filing behavior. In Section 6 we explore a causal link of accountants on their clients by analyzing the effects of audits. Section 7 concludes.

2 Conceptual Framework and Institutional Context

The turnover tax and withholding regime that will be analyzed in this paper are complex systems, with multiple provisions and special treatments that affect how different activities are taxed. Our goal in this section is to provide an overview of the system, starting from a simple setting, and then to incorporate specific institutional details.

2.1 Conceptual Framework

In this subsection we provide a simplified setting to describe the main attributes of the turnover tax and the withholding regime used for its collection and explain the incentives it generates for the different agents involved. We describe the different scenarios that might be observed in the data and link them to the relation between declared tax liability and third-party withholdings that we will be analyzing throughout the paper.

Consider a firm (for example, a supermarket) that sells goods to final consumers and buys products from a supplier. The supermarket pays monthly turnover taxes, T, based on its monthly gross revenue, R. Assume gross revenue for the firm is $R = \$100$. Every month the supermarket makes purchases to a supplier implying a cost, $C = \$50$. At the begging of the next month the firm submits a tax declaration where it states its gross revenue from the previous period and is charged a tax rate of $\tau = 5\%$. The total turnover tax liability will be $T = \tau R = \$5$.

Now assume that the tax authority determines that the supplier must act as a withholding agent. The supplier is legally obliged to participate in the tax collection regime and now becomes closely monitored by the tax authority through periodic audits, making purchases to withholding agents (C, in the case of our firm) observable information.

In this context, the monthly purchase that the supermarket makes to the supplier will now include an additional fee in concept of withholding of the turnover tax. Let the withholding rate be $\omega = 1\%$, such that the firm now pays $C = \$50 \cdot (1 + \omega) = \$50.5$. The withheld amount, $W = \$0.5$, will be remitted by the supplier to the tax authority and deposited in the supermarket's account in concept of future tax payments. The supermarket will still have a tax liability of $T = \$5$ but will have $W = \$0.5$ available as credit to cancel part of the tax liability. Hence, the supermarket will now pay $T - W = \$4.5$. In this case $T/W > 1$, the withheld amount only partially covers the tax liability and the supermarket has to disburse additional funds to cancel the total tax it owes.

Another possible scenario is that the total tax liability is smaller than the withheld amount in a given month. Consider the case in which the supermarket incurs in higher costs than gross revenue, $C = \$1000$ and $R = \$100$. The firm owes the same amount of tax as before, $T = \$5$, but has higher withholdings, $W = \$10$. In this case $T/W < 1$. The supermarket will have an outstanding credit that will be accumulated in the account, implying a financial cost for the firm that cannot use these funds for its business activity.

Finally, it might be the case that the withheld amount exactly matches the declared tax liability, that is, $T/W = 1$. This outcome can be reached under different circumstances compatible with regular business activity (for example, usual gross revenue $R = \$100$ and unusually high costs $C = \$500$, or the opposite case, usual costs for $C = \$50$ but unusually low gross revenue $R = \$10$). However, $T/W = 1$ is also compatible with under-reporting.

Consider the usual case where $R = \$100$ and costs are $C = \$50$, but now introduce the possibility that the tax authority cannot keep track of all of the supermarket's sales. This is a likely case in countries where a large part of final consumer transactions are made in cash and there exist low incentives to issue a receipt of the purchase. In this case, the supermarket can decide to under-report its gross revenue such that it minimizes the burden of the turnover tax, $\hat{R} < R$.

The existence of the withholding regime will induce the firm to under-report its gross revenue up to the point where $\hat{R} = \$10$. Here, tax liability will match the withheld amount and the firm will not have to disburse additional funds to cancel its dues. Why would the supermarket not declare $\hat{R} = \$0$? While having a tax liability below the withheld amount might be possible for some specific month, the withheld amount, $W = \omega C$, creates a floor on the declared tax liability, $\tau \hat{R}$. Filing taxes below the withheld amount will contradict third-party information and increase the probability of detection, therefore the firm will aim to report at least W.

To sum up, the lack of verifiable information in the final step of the production chain generates an incentive for some firms to under-report their true tax liability, using the only source of third-party information (the withheld amount) as a reference on the extent to which they can cheat.

2.2 Institutional Context

The turnover tax is collected by each of Argentina's 24 sub-national districts and it is determined on the basis of gross income earned by any firm selling goods or providing services within the territory of the province.[1] In the province of Buenos Aires, the setting where our study takes place, this tax constitutes the main source of revenue accounting for about 70% of total tax earnings.

Tax rates vary according to the taxpayer's activity, annual turnover from the previous year, and the location where the transaction takes place (inside or outside the province). Economic activities are classified into 791 categories that can be taxed either under a general regime or a differential regime. In the general regime, 647 of these activities are grouped into three broad categories: Wholesale and Retail, Services and Agriculture and Manufacturing. Rates are defined within each of these categories according to a three-bracket progressive tax schedule based on annual turnover from the previous year. Additionally, taxpayers operating in multiple jurisdictions, both inside and outside the province, face a special tax regime where the tax base is distributed across locations.

ARBA uses a withholding regime to collect part of the monthly tax filings. This implies that the agent responsible for remitting the tax is different from the statutory bearer of the tax. Both state institutions and firms can act as withholding agents. In the case of firms, the duty is restricted to those making intermediate purchases or sales over a cutoff based on the company's turnover on the previous fiscal year.

In practice, this regime is separated into downstream and upstream withholding but, given the nature of the industries we will analyze in this paper, we pay special attention to the downstream case.[2] Here, the payee in the transaction ("perceiving agent") withholds from the payer by adding the withheld tax to the total sale and remits it to ARBA in concept of future tax payments from the payer. The remitted funds are accumulated in the withheld taxpayer's account with ARBA and can be used to deduct from future outstanding tax liabilities. In general, firms will be able to partially pay for their tax liability by deducting the withheld amount (since the withholding rate is generally lower than the statutory tax rate and also because not all transactions are subject to withholding). However, there exist instances where the monthly liability will be lower than the withheld amount generating a credit balance in favor of the

[1] A similar tax is levied in the state of Washington, the "Business and Occupation Tax".

[2] Upstream withholding is similar to that used for the collection of personal income tax in the US. In this case the payer in the transaction ("retaining agent") withholds a fraction of the total amount of the sale and transfers it to ARBA in concept of future tax payments from the payee.

taxpayer that can be rolled over for future payments of the tax.[3]

Most firms rely on professional tax accountants to keep track of their book-keeping. Anecdotal evidence suggests that even small-scale enterprises and self-employed individuals hire accountants to manage their monthly taxes. In practice, not only they deal with the month-to-month tax filing activities but also advise their clients based on their knowledge of the tax system. It can also be the case that some firms hire an accountant's services to exploit their knowledge of tax rules and enforcement procedures as a way of minimizing payments. For example, Erard (1993) showed that tax non-compliance in the US was higher among individuals that prepared their taxes with the assistance of a professional. Differently to the US case, tax accountants in Argentina are not required to state which firms they provide professional services to, and therefore are not legally liable for the content of their clients' tax declarations. Therefore, it is plausible to think that Argentinian accountants have higher incentives to minimize their clients taxes by taking elusive and evasive measures.

3 Data

Our analysis relies on three sets of administrative data provided by ARBA. The first of these sets is the universe of monthly turnover tax filings for the 2017 fiscal year.[4]

The second set of records consists of taxpayer characteristics such as industry classification, location, and contact information. Our main interest here is contact information. Taxpayers must submit a valid email address in order to create an online profile from where they can file taxes. We identify emails that repeat across multiple taxpayers and define networks connecting them to a unique tax accountant. In principle duplicated email addresses across taxpayers could be attributed to family ties or other kinds of social linkages. However, we observe that over 70% of them repeat for three or more taxpayers, and that in the vast majority of cases these addresses contain references to accounting firms (for example, *estudio*, *contador*, or *contable*), therefore, we will simply refer to the node linking multiple firms as an

[3] Taxpayers whose balance repeatedly accumulates credits in their favor can file a complaint to ARBA requesting their withheld rate to be lowered. In principle it is also possible to file a request to be refunded the accumulated credit, however the conditions for this to take place are restrictive, among them: total total amount cannot exceed 50,000 pesos per claim (equivalent to $1,200), it can only be filed every 5 months and, as it is usual in these cases, the request for a refund automatically triggers an audit to the claiming taxpayer.

[4] We observe all fields completed by a taxpayer in a standard filing procedure: at the begging of each month firms submit a declaration stating the gross income generated over the course of the previous month, the tax liability is calculated by multiplying this amount by the corresponding tax rate, and finally, withheld amounts are displayed as credit in favor of the firm and may be deducted to from the total liability. Figure A1 shows a screen capture of the standard tax filing session. Finally, the only variable that we were not able to retrieve is the withholding rate at the taxpayer level but, anecdotally, we did confirm that the withholding rate is lower than the tax rate and only in exceptional cases they are equal.

accountant.[5] This strategy of linking firms to accountants has two potential problems. The first caveat is that contact information data is structured as a cross section, showing the latest information available for the year. This implies that we cannot detect whether firms are switching from one accountant to another in the period we analyze. The second issue is related to the method we use to identify accountants. By looking at repeated emails across taxpayers, we are only able to detect accountants that have more than one client. Hence, we cannot distinguish between firms that either have no accountant or in fact have an in-house accountant exclusively working for them.

The final set of data contains information on audits performed throughout 2017. ARBA uses a monitoring system that cross-checks information from various internal and external sources and makes it possible to detect irregularities with a certain degree of reliability. Once an irregularity has been flagged, the agency then proceeds to send out warning notifications or in-person visits to the firms. We observe the precise date when these interventions were received by the firms, allowing us to see whether they affected in any way the subsequent tax filings.

We focus our analysis on firms with non-zero total gross revenue for the 2017 period, operating within the province of Buenos Aires, and whose main economic activity is classified as: (*i*) retail sales, (*ii*) hotel and dining services, and (*iii*) transportation services. These activities represent approximately 39% of the total universe of tax filings and 51% of the total amount of taxes filed in 2017. Table 1 shows summary statistics, Panel A describes our main sample. It contains over 300,000 firms most of which file taxes every month of the year, constituting a panel at the firm-month level that contains approximately 3.5 million observations. We identify over 40,000 tax accountants, with 91% of firms being linked to one. Panel B shows descriptive statistics for the subset that is used for our estimations. We only look at accountants that have at least one bunching client, but we keep all clients from such accountants. The observations are collapsed to the firm-level. Therefore, in this case we have an accountant-firm dataset where monthly-varying outcomes, such as bunching, are redefined in terms of shares of events relative to the total number of months filing taxes.

4 Evidence of Bunching

We start by taking the ratio of the monthly tax filings to withheld amount for all the observations in our sample and group them in bins of size 0.02. Any firm whose ratio is equal to 1 is defined as "bunching".

[5] There are other ways to define networks, other papers such as Drago et al. (2018) and Boning et al. (2018) exploit geographic proximity to analyze the diffusion of information across individuals. We will also explore this possibility in our analysis in Section 5.

More specifically, given that the firm has been withheld some positive amount during a certain month, we will define it as bunching if it declares to have a gross revenue such that the ratio of total turnover tax with respect to the amount withheld by third parties falls in the interval $[0.99, 1.01]$. Bunching tax filings represent 1% of our main sample while 8% of all firms bunch at least once during the period under analysis.

Figure 1 plots the distribution of tax-filings according to their ratio. There is a noticeable clustering of filings located exactly at $ratio = 1$. As we mentioned before, this could be consistent with a firm's regular business activity. However, there are other distinctive features of the figure that suggest firms are exerting effort to locate there. Coming from the right of the distribution, there is excess mass right before the threshold is reached. This is consistent with firms trying to get as close as they can to the point where their declared tax liability is equal to the withheld funds in order to reduce the additional disbursement of funds at the moment of paying the tax. This behavior is compatible with that found by Rees-Jones (2017) for individuals filing their annual income tax in the US: loss-averse taxpayers will manipulate their taxes in order to avoid having a positive balance with the IRS.

Coming from the left, we notice two striking patterns. First, there is some missing mass right next to the threshold consistent with firms avoiding to to locate there because it could increase the probability of audit in case they were under-reporting.[6] Second, the density of filings increases as we get further away and to the right of the threshold. These tax-filings are consistent with firms being over-withheld due to regular and unavoidable circumstances in their business activity.[7]

This distribution could be consistent with a subset of firms mechanically bunching at the threshold, implying that what we observe would not be a response of taxpayers to the withholding regime but rather an outcome of how the tax system is designed. To illustrate this, consider the case of agricultural activities. Two features distinguish this sector from the retail activities we analyze in the paper. Agricultural firms predominantly operate in the first stages of the production chain with large buyers and suppliers, making it more likely that a higher fraction of their transactions are subject to withholding. In addition, the withholding rate for these primary activities is set equal to the tax rate. This implies that in many instances the withheld amount at the end of each month will mechanically be the same as the monthly liability, forcing a large fraction of the monthly tax filings to locate right at the threshold. Figure 2

[6] As mentioned in a previous footnote, ARBA will audit anyone requesting for a refund over accumulated credits. Thus, it would be unlikely for under-reporting firms to ever pass and audit given that the credit was generated through evasion in the fist place.

[7] For example, in the case of large purchases that are financed through monthly payments, the withheld amount for the total transaction is remitted in the initial period. This implies that the firm will face unusually high withholdings the first month after the purchase.

compares the agricultural sector to our sample of firms.

If the shape of the distribution documented in Figure 1 was due to mechanical reasons similar to those outlined for agriculture, we would expect some firms to persistently file taxes equal to the amount withheld by third-parties, which would in turn explain the accumulation at the threshold. To rule out this possibility we analyze the number of times a specific firm bunches conditional on having bunched once. In Figure 3 we plot the share of months firms bunch at the withholding threshold throughout the year. That is, we take a firm that locates at $ratio = 1$ in Figure 1 and count how many times this repeats for all the months it filed taxes, giving us an idea of the persistence of this behavior throughout the year. We do this for all firms at $ratio = 1$ and see the distribution of monthly repetitions across such firms. We find low persistence in bunching: of the total number of firms that locate at $ratio = 1$, 72% of them bunch in 10% of the months they pay taxes. How uncommon is this behavior relative to other firms that never bunch? To answer this question we repeat the previous exercise on every other ratio in the distribution from Figure 1. We calculate firm persistence in 476 pseudo-thresholds and plot their mean and standard deviation. The distribution for taxpayers located at the withholding threshold is similar to that of the "placebo" distributions suggesting that the persistence of firms at $ratio = 1$ is only slightly higher from other firms.

We also analyze whether the bunching is driven by tax filings from some specific month. This could be the case if firms found it more convenient to modify their reported revenue in accordance to some specific event during the year (for example, two important federal taxes that are paid annually are due between May and June). Figure 4 shows the distribution of the ratio across months, bunching behavior seems to be independent from the month.

Taken together, these results imply that the mass point we observe in Figure 1 is not driven by a specific subset of firms persistently locating at the threshold and that the incentives embedded in the withholding regime are a likely cause for firms to locate there. We argue that tax accountants could enhance a firm's knowledge of these incentives and contribute to their dissemination across their network, leading to increased bunching from their clients. A first piece of suggestive evidence is presented in Figure 5, where we show the distribution of bunching clients across accountants. While the overall share of bunching firms in the sample is approximately 8%, there is a large fraction of accountants that have an unusually large share of bunching clients. This suggests that the practice is not as unusual for the clients of some professionals which could be due to their knowledge of the incentives generated by the withholding regime.

5 The Role of Accountants on Firm Behavior

Our goal in this section is to analyze the relation between accountants and firm behavior. To do so, we evaluate whether one firm's bunching is correlated to that of the other firms sharing the same accountant. This is motivated by the fact that we cannot directly observe the effect of accountants on firm's tax-filing decisions. Then, we follow a similar procedure to Chetty, Friedman, Hilger, et al. (2011) and use the average share of bunching of the other clients from the same accountant as a proxy.

Our strategy has an important drawback. In an ideal experimental setting each firm would be randomly assigned to an accountant and we would be able to obtain an unbiased estimate of the effect we are after. However, due to the observational nature of our data, there is no random assignment of firms to accountants which will potentially bias our results. Firms who hire the same accountant are similar in many ways, and unobserved aspects of their behavior will be captured by our estimates. Since we cannot solve this issue without some additional source of variation, we will provide a series of robustness checks in order to test alternative explanations for our results.

We proceed to estimate the following specification for the effect of accountants on their clients:

$$b_{ij} = \alpha + \beta B_j^{-i} + X_i' \gamma + \varepsilon_{ij}, \tag{1}$$

$$B_j^{-i} = \frac{1}{I-1} \sum_{k=1, k \neq i}^{I} b_{ij}.$$

where $i = 1, \ldots, I$ indexes firms and j accountants. The left hand side variable, b_{ij}, is the share for months that firm i bunched (conditional on having been withheld a positive amount of tax). On the right hand side, B_j^{-i} is the share of bunching months for all of accountant j's clients excluding client i. X_i controls for zip-code and economic activity fixed effects, that capture systematic differences across locations and industries of firms, respectively. The error term, ε_{ij}, is clustered at the accountant level. As observations are collapsed to the firm level, this specification exploits the variation in bunching from one accountant to another without looking into the month-to-month variation that may occur for each professional and her clients. The estimated coefficient for β will capture any accountant-level shocks that affect their clients systematically.

Before turning to the results, it is important to stress the potential consequences of systematic sorting of firms to accountants. Even if we find that the bunching behavior of client i from accountant j is correlated with the rest of j's clients, a large part of this effect might be due to the fact that similar firms are likely to cluster among certain accountants, leading to a positive correlation between the bunching behavior of client i and other clients not because of the accountant's influence but due to some other shared characteristic across firms that we are not taking into account.

To provide a robustness check to our results, we define other dimensions on which firms might cluster and estimate Equation 1 using these alternate definitions. We construct narrowly defined variables of location and industry: for location we construct groups at the zip-code-street level, and for industries we use the most detailed eight-digit classification of the activity. We then calculate an analogous measure for the shares of bunching excluding the own-firm. The goal of estimating these specifications will be to check whether the effect found in the accountant cluster is similar to that found in these alternative definitions. If results are not very different from each other then we will be able to conclude that the effect for accountants is likely driven by other similarities that firms have. On the contrary, if the effect is an outlier, then we will have a stronger case to believe that the covariance in bunching across firms is in fact driven by their accountant.

Finally, we must also consider the potential caveats of our clustering assumption for the error term. Our decision to cluster ε_{ij} at the accountant level is based on the idea that the tax filings we observe from firms are actually managed by their accountants. If they are the ones deciding for their clients, then it is reasonable to think that firms managed by the same accountant will have correlated unobservables. However, if observations are correlated in other dimensions, failure to account for such within-cluster error correlation could lead to biased standard errors, affecting the accuracy of our statistical inference. One possible instance in which this might happen would be the case where firms have similar tax structures by accountant.

5.1 Results

Table 2 shows the estimation results for Equation 1. Columns (1) and (2) correspond to the accountant cluster, while columns (3) to (6) show the estimations for the robustness checks at the location level (zip-code-street) and industry level (8-digit-classification). All columns have the same specification where we regress the own share of bunching across months against leave-out share of bunching across months for the relevant group.

The results displayed in columns (1) and (2) are consistent with the existence of an accountant effect, the value of β is statistically significant and positive, its magnitude implies that a one percentage point increase in the share of other clients bunching is associated with approximately a one-half percentage point increase in bunching of the own client. The model, even after the inclusion of fixed-effects in column (2), can only explain a small fraction of the variation in the dependent variable.

The comparison of these results against those in columns (3) through (6) leads to some interesting insights. The correlation across firms that have the same tax professional is higher in absolute terms than that of the other two cluster definitions. This suggests that having the same accountant may be more influential on determining firm behavior than other common traits shared by firms that are located very close to each other, or by firms performing the same specific activity. The spillovers across firms located close to each other are negative while the opposite is true for the spillovers across firms in the same industry. A potential explanation for these results is that firms in the same location, even if they share strong social ties due to geographic proximity, may have inherently different cost and revenue structures related to their specific industry characteristics, leading to the observed negative correlation. On the other hand, firms in the same industry will likely have a similar business structure which in turn might be more important to explain tax-filing behaviors.

Taken together, these results provide suggestive evidence that accountants are an important factor to explain the bunching behavior observed in the tax-filings of firms. Nevertheless, it is important to take into account that we only explored two alternative explanations and there could be other dimensions that are even more relevant drivers of bunching. For instance, a very important robustness check that should be included in future extensions of this paper is to perform a permutation test by randomly assigning firms across accountants and then reestimating the coefficient of interest for multiple draws. If what matters for a firm's own behavior is their accountant, then we would expect the t-statistics for the estimate of these random permutations not to be statistically significant in most of the cases.

6 Accountants as Diffusers of Information

The evidence presented in the previous section is consistent with the existence of a positive correlation between accountants and the tax filing decisions of their customers, but the cross-sectional data does not allow us to establish any causal relation. Here, we use monthly audits in an attempt to provide evidence of an effect of accountants on their clients achieved through the diffusion of information.

A stylized description of the mechanism we have in mind is as follows. If accountants are sharing their knowledge of the tax system with their clients, we would expect that, after learning that one firm has been audited in month t, they will update their expected probability of audit and notify the rest of their clientele to modify any suspicious behavior in the subsequent periods. We use an event-study design to estimate the effect of audits on the behavior of firms. We exploit within-firm monthly variation in the audit events to see how the own-audited firms react and, more importantly, whether the peer (non-audited) firms react.

We use the same estimation sample as in Section 5 but expand it to the monthly level, bringing the total number of observations to approximately 2 million tax filings. The audit data distinguishes two different kinds of interventions: a remote audit, notified through ARBA's website, and an in-person audit, where the agency's personnel visit the firm and retrieve information on-site. For the purposes of this paper we will treat both types of audits as an analogous event. There are close to 20 thousand firms that receive some kind of treatment over the period under analysis.

One potential problem that could arise with our approach is that the audit may lead firms to change different margins of their tax-filing behavior. In particular, we are interested in looking at the likelihood of a firm bunching after an audit, but since bunching is defined by the ratio of declared tax liability to third-party withheld tax, it could be the case that a firm simultaneously modifies both of these margins after an audit. The firm could increase compliance by declaring higher revenue but also change the amount of transactions with withholding agents, making it unclear what would be the expected effect on the ratio. Additionally, as we have shown in Figure 3 the majority of firms only bunch occasionally throughout the year, so if an audit triggers a change in their bunching behavior, we might not be able to see an effect in our data. For these reasons we also specify regressions where we use tax liability and withheld amount as dependent variables.

We use the following model to estimate how firm tax-filing outcomes evolve around the time of an audit:

$$y_{ijt} = \sum_{p=-3}^{4} \beta_p \mathbf{1}\left\{P_{it} = p\right\} + \theta_i + \gamma_t + \varepsilon_{ijt} \tag{2}$$

where i, indexes firms, j accountants and t months. The left hand side variable y_{ijt} is either an indicator function taking value one if firm i bunched in month t, the logarithm of tax liability, or the logarithm of the total withheld amount for firm i in month t. P_{it} denotes a dummy variable indicating the number of periods, p, relative to the event of audit ($p = 0$). We pick the month previous to firm i's audit as our baseline period since the effects of the audit might be reflected in the same month of occurrence (recall that tax filings are done at the begging of the next month). The observation window spans eight months, with three leads and four lags. We also include in our regression firm fixed effects and calendar month dummies, θ_i and γ_t, respectively.

Given our normalization, the parameter β_p is the effect of the audit p time periods away from the event, compared to the level one period before it. Hence, the values of $\{\beta_p\}$ for $p > -1$ correspond to the effect of interest p periods after the audit and the values of $\{\beta_p\}$ for $p < -1$ can be used to test the validity of our design: under the assumption that there are no other confounds except the audit treatment affecting our outcome variable, we should observe no effects in the periods prior to the intervention.

There exist several potential problems in our estimation strategy.[8] The first concern is that our estimates for Equation 2 do not keep a balanced panel of observations throughout the periods, this may be a cause of bias if, for instance, after an audit event there is a compositional change in the kinds of firms that continue filing taxes. Another issue that might hinder our results is firms switching accountants. Recall that the data does not allow us to observe firms switching from one tax professional to another. It is a likely scenario that firms might decide to hire another tax professional after learning some peer client was audited. If this were the case, we would be attributing the effect of an event on a firm which is no longer a peer of the one that actually was audited. Nevertheless, this effect may only become relevant after longer periods of time. Finally, our estimation model only allows for variation of the treatment effects relative to the time of treatment, implying that the effects will be homogeneous across firms and months. We would expect the effect to be stronger for firms more likely to be under-reporting taxes. For instance, in future extensions of this project, it would be interesting to see if the treatment effect varies for firms that are at either side of the threshold imposed by the withholding regime.

6.1 Results

Figure 6 shows the estimation results for the effect of an audit on the own firm. The first panel shows that the propensity of the firm to bunch in a given month remains unaltered by an audit. This result is rather unsurprising given the fact that in Figure 3 we showed that there is generally low persistence in bunching across firms. It might still be the case that audited firms change their bunching behavior in subsequent periods but the effect may be too small to be captured in the short interval of time we are analyzing.

We turn to the two other panels in Figure 6 to determine if there is any response from firms after an audit. Declared tax liability jumps sharply at the time of audit, declarations increase by .05 log-points for

[8] Unfortunately, we were not able to address these issues before the presentation of the paper due to a malfunctioning of the server.

the first two periods and then decrease to about .01 log-points in the fourth month after the audit. Looking at the pre-periods, there is a negative effect two months prior to the audit. This could be explained by the fact that audits are not random and firms that were declaring gross revenues below what was expected by the tax authority are more likely to be targeted. The firm's total withholdings by third-parties also increase, initially by .06 log-points and then stabilize around half that amount. One potential explanation for the increase in withholdings is that audited firms that were avoiding purchases from withholding third parties now rely more on them. Another possibility is that the audit deters collusive behaviors between firms and their suppliers, who now have to report all sales under the withholding regime.

Figure 7 shows the estimation results for peer audits. In other words, these estimates show the response of firms who are not audited throughout 2017, but who share the same accountant with an audited firm. Our hypothesis is that such firms will only react to an audit if accountants diffuse their knowledge of an increased probability of audit to them.

The first panel displays a similar result to the own-audit case, monthly bunch patterns are generally not affected by an audit (the increase in $t = 0$ is statistically significant but very small). The other two panels show results consistent with our hypothesis: non-audited firms react to audits by increasing their tax declarations and withholdings. Surprisingly, the magnitudes of the effects are only slightly smaller than the response documented for the own-audits. If it is the case that accountants have a causal effect on the behavior of their clients, the previous remark could be explained by the fact that these firms were also behaving similarly to the targeted firm, both before and after the audit. Another possibility is that this response is mostly driven by non-audited firms that were nevertheless incurring in some kind of avoidance or evasion behavior, in this case it becomes clear how important it would be to incorporate heterogeneous behavioral responses.

One final observation applicable to both own- and peer-audit cases is that all effects on tax-filing behavior are very short-lived. Four months after the audit, tax declarations and withheld amounts are practically at the same level as they were in the in the period right before the event took place. This interesting fact could be indicative that firms are not behaving as Expected Utility Maximizers (as in the Allingham and Sandmo (1972) model), otherwise they would update their perceived probability of audit upwards and increase compliance for the subsequent periods. The evidence shown in this section would be more in line with the "Bomb Crater Effect" introduced by Mittone (2006): after the audit occurs, firms assume that new audits are unlikely to happen and take the risk of returning to their previous behavior in the following periods.

7 Conclusion

Taxation literature has generally focused on the direct relationship between the government and taxpayers. In this paper we have shown that tax professionals may have a predominant role by meditating the tax avoidance and evasion decisions their clients make and by enabling the dispersion of information to a broader population. We have analyzed this in the context of a complex tax and tax-collection-system in Argentina, where the relative gain of having and expert's advice might be more important given the implicit incentives of the withholding regime.

These results have a number of implications. First, the use and effectiveness of third-party reporting has clear limitations that depend on the amount of information that the tax authority can observe. In economies similar to the Argentinian case, where many businesses remain on the margin of the informal economy, the government's enforcement capacity can be affected if firms adjust margins that remain unobserved. Therefore, third-party information should not be thought of as an all-encompassing solution to evasion and avoidance problems. Second, governments should consider targeting part of their enforcement efforts on accountants. Consider first our results on the correlation of bunching across clients. We have shown that bunching constitutes evidence of tax evasion on certain circumstances and that accountants matter for explaining this behavior. This implies that certain accountants could be specializing in these techniques to reduce their clients tax liability. Tax authorities should use this behavior as a tag on the underlying type of an accountant and could implement enforcement tools directly targeted to these professionals, increasing the compliance of all the taxpayers under their influence. In addition, our results on the peer's reaction to audits suggest another reason why targeting accountants should be a priority. By diffusing information, there is a broader set of taxpayers that learn about the tax authority's enforcement measures. Targeting audits to taxpayers who are part of large networks might be a cost-effective way of increasing compliance of a broader population of clients.

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Tables

Table 1: Descriptive Statistics

Panel A: Main Sample					
	mean	median	sd	p10	p90
Declaration	5.15	0.60	41.99	0.10	8.27
Withheld	5.47	0.50	45.41	0.00	9.26
Ratio	35.17	0.96	4741.25	0.22	6.45
	Num. Obs.	% Bunch.			
Tax-Filings	3,551,499	1.0			
Firms	319,340	8.2			
Accountants	43,450				
Panel B: Estimation Sample					
	mean	median	sd	p10	p90
Declaration	4.82	0.68	29.03	0.17	8.70
Withheld	5.20	0.68	29.60	0.00	9.79
Ratio	35.37	1.21	938.50	0.44	11.02
Share Bunching Months	0.135	0.083	0.141	0.083	0.200
	Num. Obs.				
Firms	191,828				
Accountants	11,680				

Notes: Panel A of this table reports summary statistics for the main sample which includes all firms whose activities are classified as: (*i*) retail sales, (*ii*) hotel and dining services, and (*iii*) transportation services. We restrict the sample to firms that report non-zero gross revenue for the 2017 fiscal year. Declaration and Withheld amounts are expressed in thousands of pesos.

Panel B of the table reports summary statistics for the estimation sample, which is a subset of the main sample where we keep all accountants that have at least one bunching client. In this case Declaration, Withheld amount, and Ratio are averaged values across months for each firm.

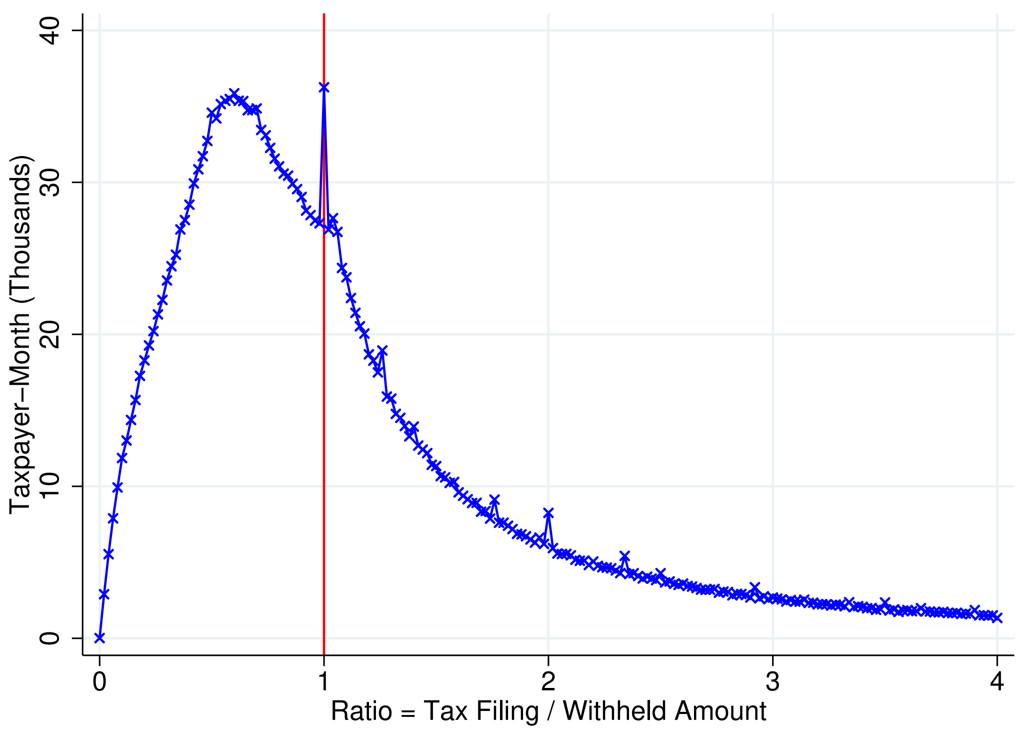
Table 2: Firm effects

	Accountant		Location		Industry	
	(1)	(2)	(3)	(4)	(5)	(6)
Bunching Others	0.504***	0.493***	-0.053**	-0.054**	0.188***	0.116***
	(0.080)	(0.081)	(0.022)	(0.022)	(0.043)	(0.041)
Constant	0.008***	0.008***	0.020***	0.020***	0.011***	0.012***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
R^2	0.0607	0.0645	0.000493	0.000901	0.00230	0.00681
N.Obs.	174498	174434	157082	157082	249445	249445
N.Clust.	10676	10676	12306	12306	6682	6682
Activity FE		yes		yes		
Location FE		yes				yes

Notes: All columns report OLS estimates with standard errors clustered at the accountant level, zip-code-street level and 8-digit industry code, respectively. The dependent variable for all specifications is a continuous variable indicating the share of months firm i bunched throughout the year. The explanatory variable varies depending on the effect of interest. In columns (1) and (2) it shows the share of bunching months for all of accountant j's clients except client i. In columns (3) and (4) it shows the share of bunching months for all firms located at the zip-code-street j except firm i. In columns (5) and (6) it shows the share of bunching months for all firms who share industry code j except firm i. *, **, *** denote statistical significance at the 10, 5 and 1 percent level.

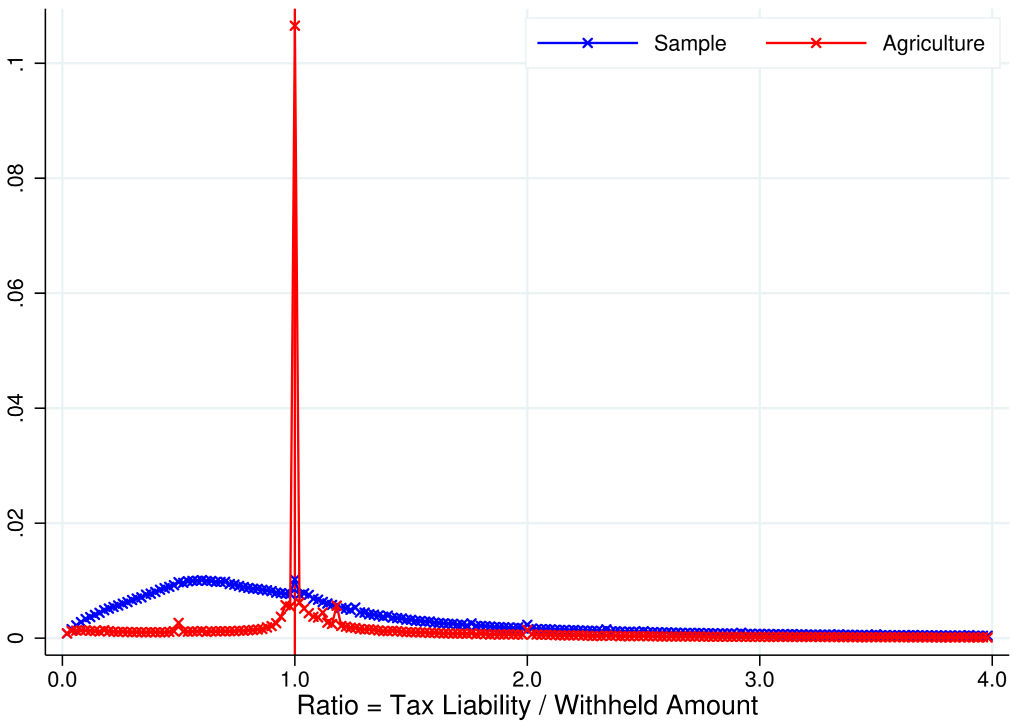
Figures

Figure 1: Distribution of Tax Filings to Withheld Amount Ratio



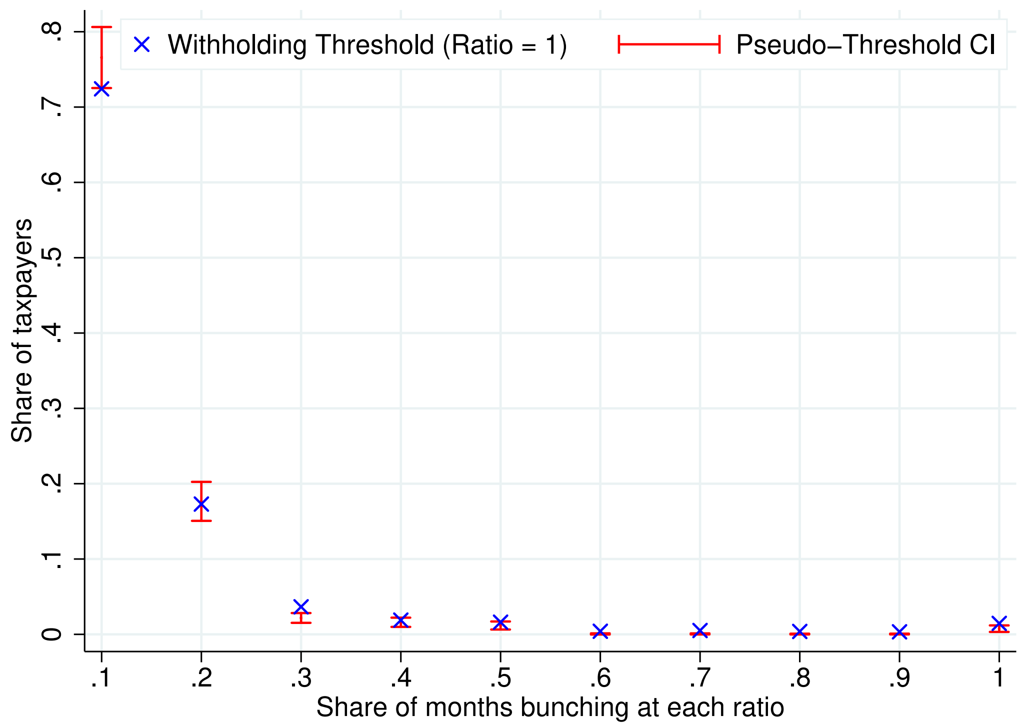
Notes: The Figure plots the distribution of the ratio of tax filings to withheld amount. We calculate it for all tax filings in our main sample, conditional on having positive withholdings in the month. The total sample contains 3,551,499 filings for 332,287 firms. The ratios are grouped into bins of size 0.02. The 5 to 95 percentile range of the bins is $[0.2, 18.04]$.

Figure 2: Comparison Between Retail Activities and Agriculture



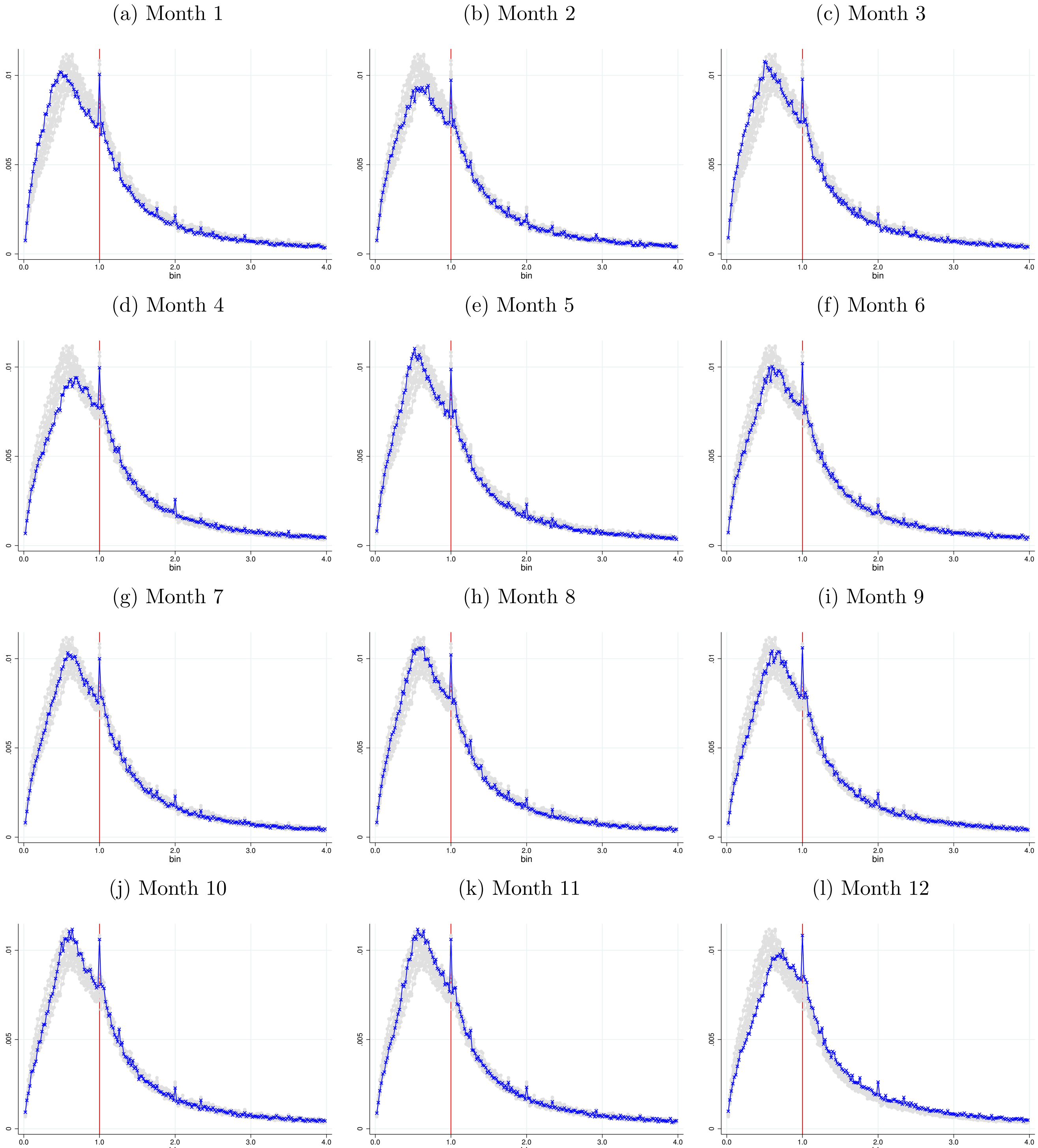
Notes: In this case the y-axis is the density of tax filings, not the total number as in previous cases. The distributions are cut at $ratio = 4$, but have a long right tail.

Figure 3: Bunching Frequency for Firms



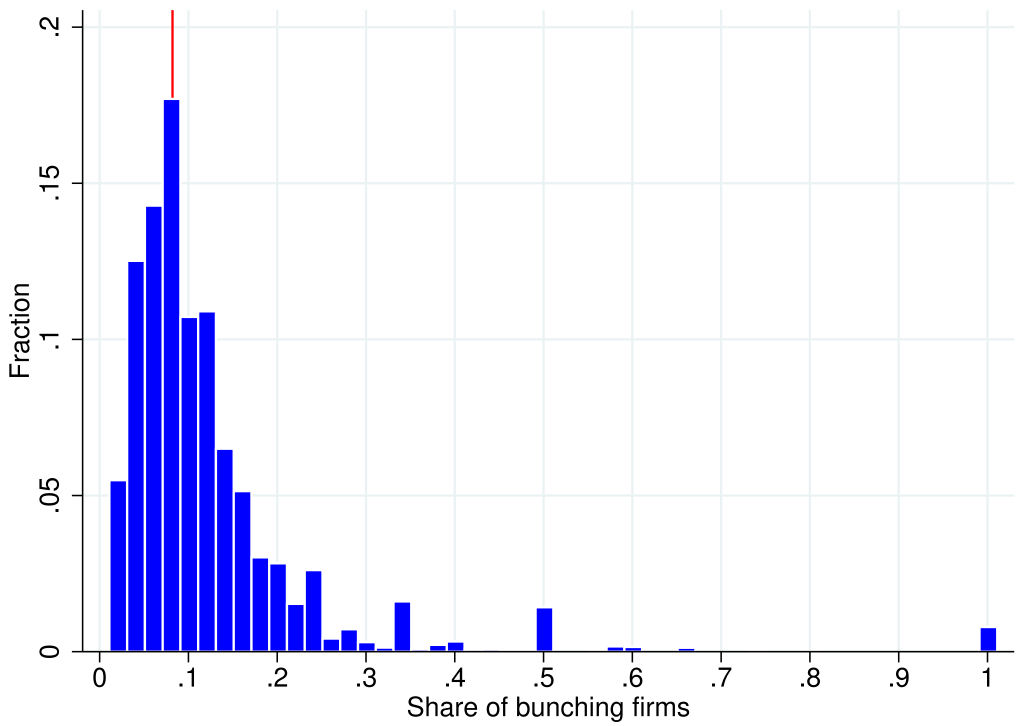
Notes: We take all firms that bunch at the withholding threshold, $ratio = 1$, and count the number of months they locate at that ratio. In the x-axis we plot the share of months bunching and in the y-axis the share of firms. We then calculate these shares for all ratios in the 5th to 95th percentiles of the distribution of ratios, adding up to a total of 476 pseudo-thresholds. We show the mean and standard deviation of these pseudo-thresholds.

Figure 4: Distribution of Tax Filings to Withheld Amount Ratio



Notes: In this case the y-axis is the density of tax filings, not the total number as in previous cases. Each plot shows the distribution for the corresponding month highlighted in blue, and the distributions for the remaining months in a gray tone.

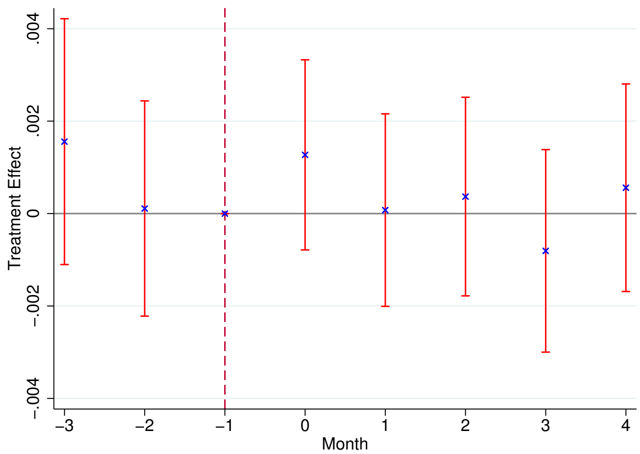
Figure 5: Share of Bunching Clients



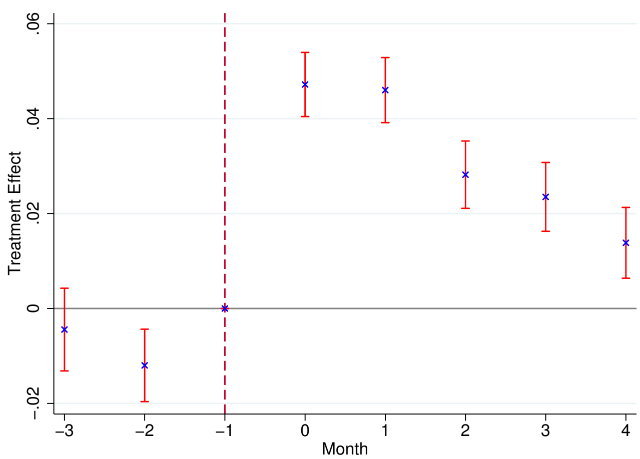
Notes: The Figure shows the distribution of the share of bunching clients across accountants, conditional on having bunching clients. Each observation is weighted by the number of clients. The vertical line in red shows the sample mean of bunching firms, equal to .082.

Figure 6: Event Study. Own Audit

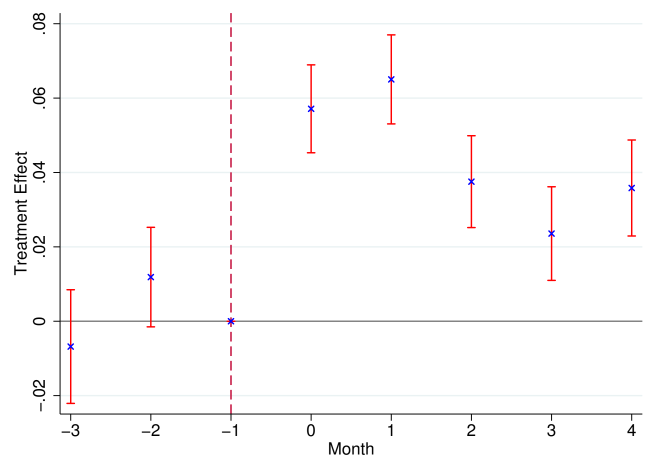
(a) Bunching



(b) Declared Tax Liability



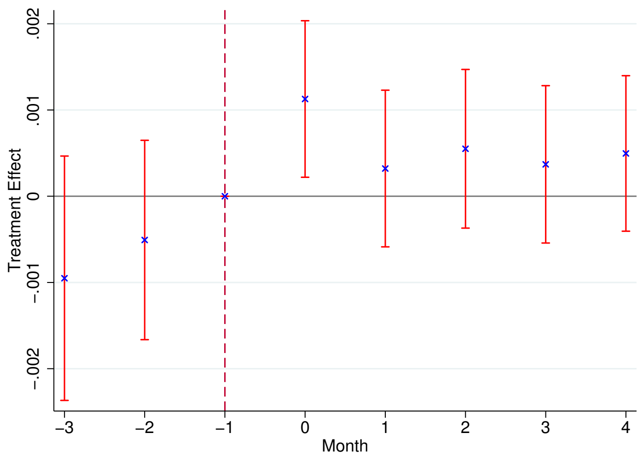
(c) Total Withheld Amount



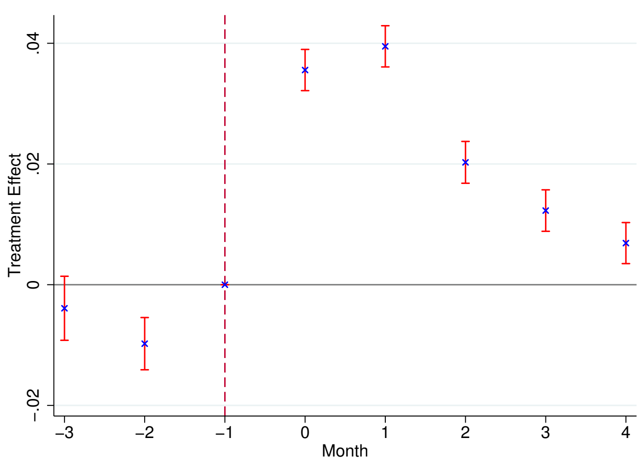
Notes: The figure shows point estimates for event time dummies (with 95% confidence bands) obtained from a model with individual fixed effects, calendar time dummies and a full set of event time dummies (where the audit event is month 0 and month -1 is the omitted category). The outcomes are: an indicator function taking value 1 if firm i bunched in month t, declared tax liability (in logs), and total withholdings by third-parties (in logs). The outcomes in this case correspond to the own firm who was audited.

Figure 7: Event Study. Peer Audit

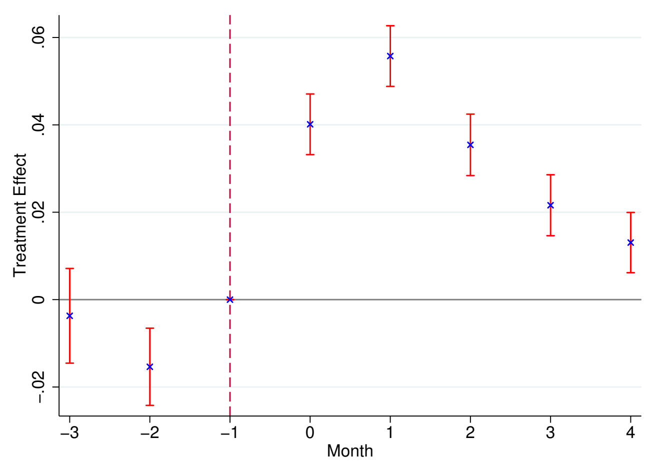
(a) Bunching



(b) Declared Tax Liability



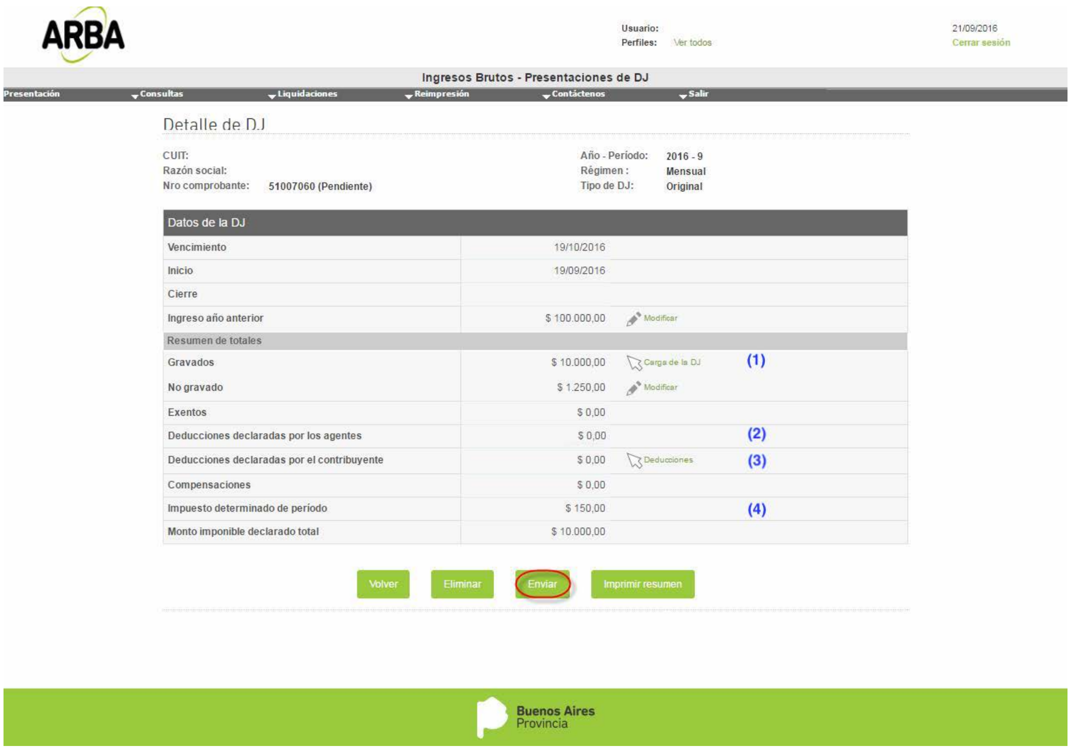
(c) Total Withheld Amount



Notes: IThe figure shows point estimates for event time dummies (with 95% confidence bands) obtained from a model with individual fixed effects, calendar time dummies and a full set of event time dummies (where the audit event is month 0 and month -1 is the omitted category). The outcomes are: an indicator function taking value 1 if firm i bunched in month t, declared tax liability (in logs), and total withholdings by third-parties (in logs). The outcomes in this case correspond to non-audited firms who share the same accountant as the audited one.

Appendix A: Additional Tables & Figures

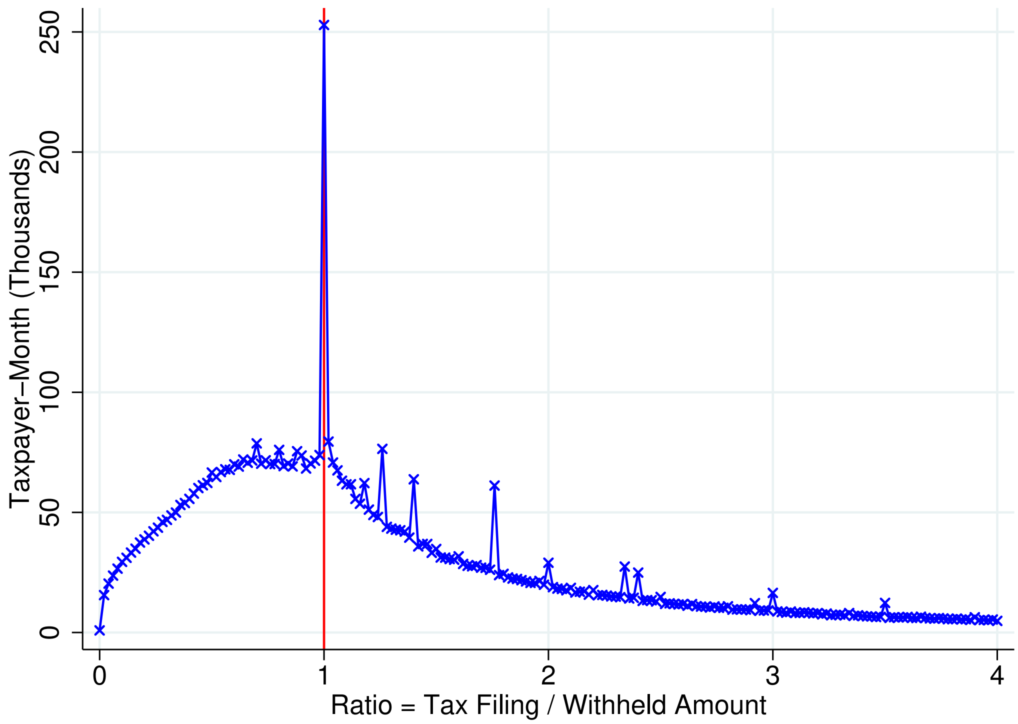
Figure A1: ARBA's Turnover Tax Filing Web Page



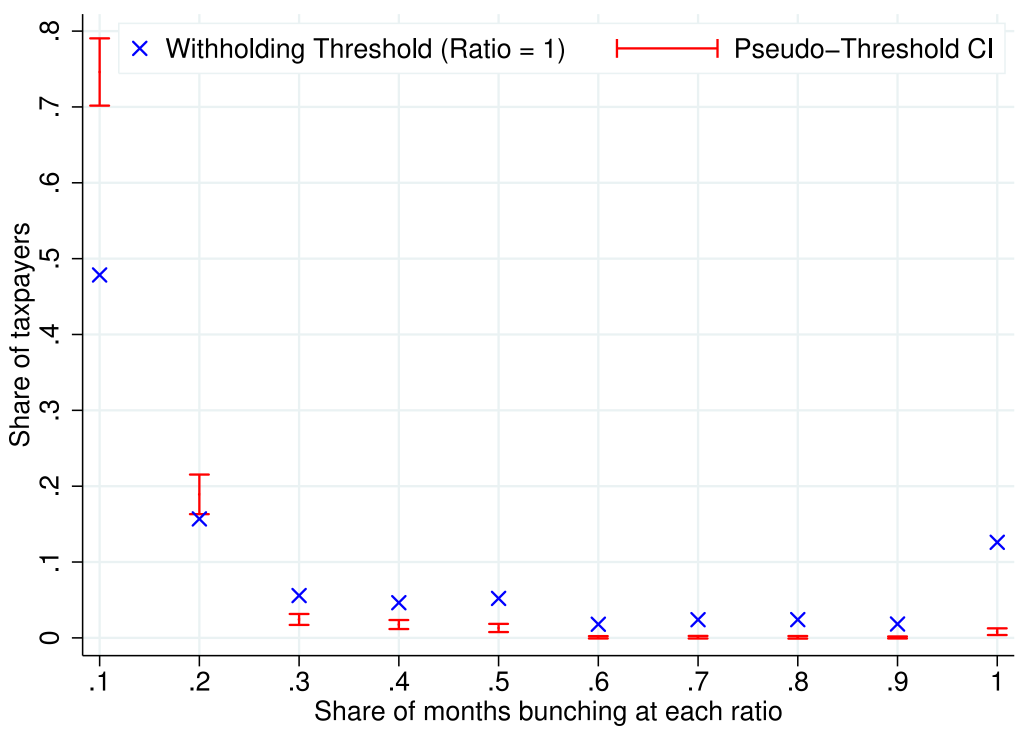
Notes: The figure shows the screen taxpayers see when filing their monthly tax. References: (1) Total declared revenue, amount is filled by the taxpayer by uploading sales receipts from the corresponding month; (2) Total withheld amount by third parties, comes pre-loaded for the taxpayer; (3) Additional withholdings from third parties, uploaded by taxpayer; (4) Total tax liability, is the result of multiplying the declared revenue by the corresponding tax rate minus the withheld amounts. The remaining lines correspond to exemptions (not included in our analysis, since they correspond to taxpayers with activities in other provinces) and compensations (firms obliged to withhold form third parties are partially compensated for their duties).
Source: Tax Filing Tutorial, ARBA

Figure A2: Figures for Full Dataset

(a) Distribution of Tax Filings to Withheld Amount Ratio



(b) Bunching Frequency for Firms



Notes: This figure reproduces Figures 1 and 3 for the full dataset containing all tax-filing and activities, totaling approximately 8 million tax filings.