Consumers as Tax Auditors

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Abstract

Access to third-party information trails is widely believed to be critical to the development of modern tax systems, but there is limited direct evidence of the effects of changes in information trails. This paper investigates the enforcement effect of an increased availability of third-party information, and sheds light on how governments can harness this information despite collusion opportunities. I exploit unique administrative data on firms and consumers from an anti-tax evasion program in Sao Paulo, Brazil (*Nota Fiscal Paulista*) that created monetary rewards for consumers to ensure that firms report final sales transactions, and establishes an online verification system that aids consumers in whistle-blowing firms. Using variation in intensity of exposure to the policy, I estimate that firms' reported revenue increased by at least 22% over four years. The compliance effect is stronger for firms that face a high volume of consumers, consistent with positive shifts in detection probability from whistle-blower threats. I also investigate the effect of whistle-blowers directly: firms report 14% more receipts and 6% more revenue after receiving the first consumer complaint. To study the role of the value of rewards in improving enforcement, I show evidence consistent with the possibility that lottery incentives amplify consumer responses due to behavioral biases, which would make it more costly for firms to try to match government incentives in a collusive deal.

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Tax revenue as a share of GDP is substantially higher in modern advanced economies than in the early 20th century or in present-day developing countries (Besley and Persson, 2014). A key source of the variation in tax revenue is the enforcement capacity of governments.[1] In particular, a growing literature emphasizes that information on taxable transactions shared with third-parties can be leveraged by governments to ensure more accurate self-reporting,[2] and that the increased availability of third-party information trails as countries develop could help explain the dynamics of government revenue among advanced economies during the last century (Gordon and Li, 2009; Kleven, Kreiner and Saez, 2015).

Despite the empirical literature on the deterrence effect of third-party reporting, there is little direct evidence on whether changes in availability of information trails can improve compliance and on the mechanisms through which third-party reporting deters evasion, as it hinges on avoiding collusion opportunities among the informed parties.[3] This paper exploits quasi-experimental variation and unique administrative data on firms and consumers from an anti-tax evasion program in Sao Paulo, Brazil – *Nota Fiscal Paulista* (NFP) – that created monetary rewards for consumers to ensure that firms report final sales transactions. The program provides tax rebates and monthly lottery prizes for consumers who ask for receipts, and establishes a direct communication channel between the tax authority and consumers through an online account system, where consumers can verify receipts reported by establishments and can act as whistle-blowers by filing complaints.

The program was designed to address the 'last mile' problem of the self-enforcing

[1]Musgrave (1969) emphasized the historical relevance of tax administration for tax collection. In the policy debate, tax administration and the enforcement capacity of developing country governments are central issues (Slemrod and Gillitzer, 2014; Bird and Gendron, 2007; IMF, 2011).

[2]Audit experiments typically detect near zero evasion in income subject to third-party reporting (Kleven, 2014; Pomeranz, 2015; Slemrod et al 2014; Kleven et al, 2011). For instance, wage earners would face a much higher risk of audit relative to the self-employed if they under-report income, as firms typically also report wages paid to the government (Slemrod, 2007). More generally, information trails shared with third-parties such as employees, suppliers, banks or customers could have a deterrence effect even if they are not systematically reported to the government. Evidence from Denmark and the U.S. suggests that even when income is not subject to systematic third-party reporting, compliance is well below full evasion, which could be explained in part by the existence of derivative information shared with third-parties (Kleven, 2014).

[3]This is a well-known issue in the mechanism design literature (e.g., Tirole, 1986): once more than one person is informed about evasion then there are many mechanisms that can be used to elicit that information (Besley and Persson, 2013). A key assumption in these cases is that there is no scope for collusion among the informed parties. For instance, Yaniv (1993) argues that employers and employees can find mutually beneficial opportunities to reduce their tax liabilities, which would result in limited enforcement effect on self-reports of individual income subject to cross-reporting by firms.

mechanism of the Value Added Tax (VAT). Along the supply chain, the tax credit and debit system of the VAT generates third-party reporting in transactions across firms.[4] At the final consumer stage, however, these self-enforcing incentives break down since consumers typically derive no direct monetary benefit from asking for receipts.[5] The NFP policy introduced incentives similar to the VAT for final sales: it aims to affect both the likelihood that a transaction is reported at all, and the accuracy of reporting, since rewards to consumers are an increasing function of the value of receipts.[6]

I begin the analysis describing a conceptual framework to discuss how incentives to consumers can affect firm behavior. The NFP policy is effectively increasing the availability of third-party information trails through rewards to consumers, but collusion between consumers and firms could hinder the self-enforcing effect of third-party information. However, in order to collude with consumers and continue evading, firms would need to transfer part of evasion rents to consumers through discounts. Moreover, firms would reveal evasion information to many third parties by conditioning the discount on not accurately reporting the transaction to the government. As in Kleven, Kreiner and Saez (2015), the difficulty in sustaining collusion with a large number of informed economic agents who can act as whistle-blowers might be important to deter evasion. Therefore, the effect of consumer monitoring should be stronger the higher the threat of whistle-blowing, and the more firms need to transfer to consumers to match the value of the rewards offered by the government.

In order to empirically investigate the extent to which rewards to consumers can affect firm compliance, I construct unique administrative data on establishment-level monthly tax returns, monthly individual-level data on requested receipts and overall participation in the NFP program, based on administrative records from the tax authority of the state of Sao Paulo.[7] I divide my analysis into three parts. First, I study the effect of consumer monitoring on establishments' compliance by exploiting variation in the intensity of expo-

[4]Most countries in the world adopted the VAT instead of sales tax, perhaps because of its enforcement advantage (Keen and Lockwood, 2010). Kopczuk and Slemrod (2006) argue that retail sales tax and the VAT are theoretically equivalent, but the VAT has built-in enforcement incentives along the supply chain. Pomeranz (2015) provides empirical evidence for the self-enforcing properties of the VAT.

[5]Slemrod (2007) refers to the enforcement problem at the final consumer stage as the 'Achilles heel' of administering a retail sales tax: if firms collude to underreport transactions, the self-enforcing mechanism can unravel, and may hinder tax collection across the entire chain.

[6]Both the tax rebate and the number of lottery tickets with which consumers are rewarded are a function of the total amount they spend in a given month as detailed in section 2.2.

[7]A number of measures were taken to de-identify the data in order to protect confidential tax records. See section 2.3

sure to the policy. I compare reported revenue changes in establishments that sell mostly to final consumers (retail) versus establishments that sell mostly to other firms (wholesale). I estimate that reported revenue in retail increased on average by 22% over four years as a result of NFP. This estimate is likely to be a lower bound for the effect of the program, given that wholesale establishments may also have been affected by the change in consumers' decisions to ask for receipts.[8]

Second, I shed light on mechanisms by examining the implications from the conceptual framework for firms subject to higher whistle-blower threats, and by discussing the role of rewards offered by the government on consumer participation in the enforcement policy. I find evidence consistent with the argument that collusion might be difficult to sustain if consumers can blow the whistle. Establishments in sectors that are characterized by a large number of transactions that would be more exposed to potential whistle-blowers are relatively more affected by the consumer rewards program. Furthermore, I link consumer participation to firm compliance by exploiting the timing of consumers' whistle-blowing and find that firms report 14% more receipts and 6% more revenue after receiving the first complaint.

Next, I turn to the effects of rewards on consumer participation. As suggested by the conceptual framework, the more consumers value the rewards, the more costly it will be for firms to try to match the government's incentives. I exploit variation from lottery prize rewards from NFP to analyze changes in the number of receipts for which individuals ask and the number of different businesses in which they ask for receipts. I find that consumers condition their decisions to ask for receipts on past lottery wins. Even when prizes are as small as U.S. $5, winners ask for receipts more often and in a larger set of establishments for at least three months after the lottery result relative to non-winners with the same odds of getting a prize. The results are consistent with the possibility that lotteries amplify consumer engagement due to behavioral biases.

In the final part of the paper I discuss policy implications. A number of countries reward consumers to ask for receipts to address the last-mile problem of the VAT.[9] Through

[8]Wholesale firms can sell to final consumers directly, in which case the rewards program applies. Additionally, improving compliance among retail firms can affect compliance by wholesalers through the self-enforcing mechanism of the VAT.

[9]For instance, Argentina, Bolivia, Brazil, China, Chile, Colombia, Indonesia, Italy, Portugal, Puerto Rico, South Korea and Slovakia, among other countries, have introduced policies to address the enforcement problem downstream through monetary incentives – through tax refunds, lotteries, or fines – for consumers to request receipts (Fooken et al, 2014; Bird, 1992; Cowell, 2004; Fabbri, 2013; Marchese, 2009).

these policies, governments are foregoing a fraction of both marginal and infra-marginal revenue. If agents can perfectly collude, these programs would not generate infra-marginal revenue. The degree to which reward programs can improve revenue collection, therefore, hinges on frictions to collusion such as whistle-blower threats and consumers' response to lotteries in the Sao Paulo case. I also discuss other potential costs and benefits associated to such policies.

This paper contributes to a growing literature that argues that third-party information is key for compliance (Gordon and Li, 2009; Kleven et al., 2011; Pomeranz, 2015, Kumler et al., 2015, Jensen, 2016). In particular, it provides evidence from changes in the availability of third-party information trails and the results are consistent with the whistle-blower mechanism suggested by the theoretical model in Kleven, Kreiner and Saez (2015). Additionally, the paper contributes to the literature on the challenges of taxation in developing countries. In particular, a growing strand of the literature sets aside non-compliance due to firm non registration at the tax authority – the formal-informal margin – and instead examines non-compliance among formal firms.[10] More generally, the paper is related to a vast literature on tax evasion and enforcement (e.g., Andreoni et al., 1998; Slemrod and Yitzhaki, 2002).

Finally, the paper contributes to the policy debate on sales tax enforcement.[11] This paper provides, to my knowledge, the first direct evidence of consumer behavioral responses to rewards from asking for receipts. The results also reinforce existing findings on individual responses to lotteries that are used as levers in other contexts, such as lottery-linked savings (Tufano, 2008; Kearney et al., 2011). Moreover, the evidence from the NFP lotteries adds to the literature on the behavioral effects of lottery wins such as the lucky store effect (Guryan and Kearney, 2008). More generally, the paper sheds light on how participatory policies can be used as a monitoring tool.

The remainder of the paper is organized as follows. Section 1 outlines a simple conceptual framework to guide the empirical analysis. Section 2 describes the institutional background of the *Nota Fiscal Paulista* program, the relevant datasets, sample definitions and summary statistics. Section 3 investigates the enforcement effect of the introduction of third-party information through consumer rewards on firms's reported revenue, and

[10] De Paula and Scheinkman (2010) argue that better enforcement in the intensive margin of VAT systems can endogenously generate incentives to formalize by creating supply chains of formal firms. See Bruhm and McKenzie (2013) for a review of the literature on the formalization of firms.

[11] Wan (2010) argues that a program that turns receipts into lottery tickets in China was effective in raising tax revenue, but the evidence for such policies is mixed (Barroso and Cortez, 2009; Mattos et. al, 2013).

section 4 sheds light on mechanisms suggested by the conceptual framework regarding whistle-blower threats and the value of monetary rewards. Section 5 examines policy implications, and section 6 concludes.

1 Conceptual framework

I begin by describing a simple conceptual framework that examines the degree to which consumer monitoring can affect the evasion decision by firms. I follow a Becker (1968) crime model developed by Allingham and Sandmo (1972) to analyze tax evasion. In particular, the framework uses a variant of this model discussed by Kleven et al. (2011), in which the probability that a taxpayer is caught evading depends on the audit rate and the probability of detection conditional on audit. First, I present a baseline case with government monitoring only. Then, I introduce consumer monitoring as an additional enforcement tool that gives rewards for consumers to ensure firms report final sales transactions, and allows consumers to act as whistle-blowers. In this case, firms may continue evading by colluding with consumers. In doing so, however, firms get a lower benefit from evasion and reveal to a number of third-parties evasion information that the government may access through whistle-blowers.[12]

1.1 A tax evasion model

Consider a risk-neutral firm that pays a tax $\tau \in [0,1]$ proportional to their reported revenue $Y \geq 0$. Suppose firms sell a single product, and that each firm has N consumers who each make one purchase that generates revenue $\bar{y} \geq 0$. Firms have a true pre-tax revenue $\bar{Y} = N\bar{y}$, and choose to report revenue Y to maximize profits π.

Government monitoring only. Let $p \in [0,1]$ be the probability of detection faced by the firm. Similarly to Kleven et al. (2011), I consider that the audit probability is increasing in the amount evaded, and that the probability governments detect evasion is a product of government audits and the likelihood that the government will uncover evasion by taxpayers during an audit. Kleven (2014) argues that the more derivative information from

[12] I take a positive approach to understand the effects of different monitoring tools on firms evasion decision. For a normative approach, see Arbex and Mattos (2015) that investigate how the Ramsey equation is modified once consumers are rewarded to ask for receipts. They find that welfare is higher when consumer auditing is added to the usual direct government auditing.

various third party sources is available to tax enforcement, the more compliance we observe despite low audit rates. The intuition is that the more information the government has about the firm, the easier it is to detect evasion conditional on audit (Slemrod, 2007).

Let $a(E) \in [0,1]$ be the audit probability, $E = \bar{Y} - Y$ be the total evasion by firm, and $d \in [0,1]$ be the ability of the government to detect evasion in an audit. The probability of detection faced by the firm can be written as $p \equiv a(E)d$, $p'(E) = a'(E)d > 0$. If the firm is caught evading, the government applies a fine $\theta \geq 0$ in proportion to the evaded tax $\tau(\bar{Y} - Y)$. For simplicity, assume that in the absence of monetary incentives, consumers do not ask for receipts and have no impact on the evasion decision of firms. Thus, firms report revenue Y to maximize:

$$\pi = (\bar{Y} - \tau Y)(1-p) + [\bar{Y}(1-\tau) - (\bar{Y} - Y)\theta\tau]p \tag{1}$$

An interior optimal solution Y^* satisfies the first order condition $d\pi/dY = 0$:[13]

$$[a(E) + a'(E).E]d(1+\theta) = 1 \tag{2}$$

where $E = \bar{Y} - Y$. The right hand side of equation (2) is the marginal benefit of evading an extra dollar, and the left-hand side is the marginal cost of evading that extra dollar. As discussed in Kleven et al. (2011), the firm that evades an extra dollar incurs in a higher probability of audit of all infra-marginal dollars evaded. Firms choose the optimal Y^* that satisfies equation (2), and Y^* will be increasing in the detection probability *d*.

Adding consumer monitoring. Consider now the case where consumers can be used to monitor firms in addition to the government monitoring. Consumers are rewarded with $\alpha \in [0,1]$ of the tax τ firms pay on the transaction reported to the government. Consumers can ensure they receive this reward by requesting a receipts, and they can act as whistle-blowers by informing the government about firms' non-compliance. The aim of adding these features is to discuss the role of monetary rewards in increasing information trails about firms' evasion, and the relevance of whistle-blower threats as a device to harness this information.

I describe a case in which firms may try to collude with consumers to avoid issuing receipts with the true value of the transaction. As the government is rewarding consumers with a fraction of what firms pay in taxes, firms and consumers could potentially agree

[13]The second-order condition is $-2a'(E) - a''(E)E < 0$. It is sufficient that $a(E)$ is convex.

to a mutually-beneficial deal and not issue receipts.[14] For simplicity, assume that firms make a take it or leave it discount offer to consumers to continue reporting y instead of the true amount $\bar{y}$, and that consumers accept a discount deal that matches the government's reward $\alpha\tau(\bar{y}-y)$.

It is important to note that not only must the firm share part of their evasion rents with the consumer, the firm reveals to a third party that it evades taxes by conditioning the discount on not reporting the true amount of the transaction. Consumers, therefore, become informed third-parties. As consumers can act as whistle-blowers, governments may gain access to relevant information about firms' evasion. Thus, the firm might face an increased detection probability if consumers cannot commit not to whistle-blow.[15]

Kleven, Kreiner and Saez (2015) argue that a key deterrent of collusion is the sheer number of internal or external parties to which a firm that evades taxes exposes itself. I will consider the case where there is a probability of a random shock between the parties that can trigger a consumer to blow the whistle. A random shock could be generated by some conflict between the consumer and the shopkeeper, or a moral concern of the consumer. Therefore, the larger the number of consumers N, the higher the additional risk of detection introduced by consumes acting as whistle-blowers.

Assume $\varepsilon > 0$ is the probability that such a random shock occurs; let ε be i.i.d. across consumers. Assume that if one consumer blows the whistle on the firm the information she provides allows the government to detect evasion with certainty in an audit, and that all the N consumers may blow the whistle. The intuition is that consumers are gathering relevant information about evasion conducted by firms that can improve the enforcement capacity of the government for a given audit rate. So the ability of the government to detect evasion under consumer monitoring can be written as $d_c = 1-(1-d)(1-\varepsilon)^N \geqslant d$. Therefore, firms face an increased probability of getting caught p_c given by $p_c = a(E)[1-(1-d)(1-\varepsilon)^N]$[16]

[14]Tirole (1986) discusses the collusion problem in auditing contracts in which a group of informed parties – the auditor and the agent – can manipulate the information reported to the principal. This context is also similar to the case of corruption with theft in Shleifer and Vishny (1993), and administrative corruption in Flatters and MacLeod (1995).

[15]In the empirical context, it is particularly salient that a collusive deal will allow the firm to evade taxes since the government is giving a reward for consumers to ask for receipts in a campaign against tax evasion. Also, as will be described in detail in section 2, consumers can be whistle blowers by filing complaints about specific firms to the government through a website.

[16]It is possible that whistle-blowers affect the audit probability as well, and an alternative model could be written in line with Kleven, Kreiner and Saez (2015) that assumes that one whistle-blower triggers a full audit. The empirical implications in the next sections would be similar. Because information about audit

Now firms choose Y to maximize:[17]

$$\pi = (\bar{Y} - \tau Y)(1 - p_c) + [\bar{Y}(1 - \tau) - (\bar{Y} - Y)\theta\tau]p_c - (\bar{Y} - Y)\alpha\tau \tag{3}$$

As mentioned above, under the new policy, firms have to transfer part of the evasion rents to consumers through discounts. An interior optimal solution Y^{**} satisfies the first order condition $d\pi/dY = 0$:

$$[a + a'(E).E]d_c(1 + \theta) = 1 - \alpha \tag{4}$$

The equation highlights two ways in which the firm's evasion decision is affected by rewards to consumers. First, the marginal benefit of evading an extra dollar is reduced by α. Therefore, the costs of collusion enter as an extra penalty for each dollar evaded. In this case, the more consumers value the rewards α, the higher this extra-penalty will be. Second, if consumers cannot commit not to whistle-blow, the new detection probability will be increasing in the number of consumers N as it increases the chances consumers will inform the government about the evasion activity of firms. The empirical exercises will focus on these two dimensions of firms' evasion decision.

1.2 Comparative statics for empirical analysis

The reported revenue Y^* that satisfies the optimal compliance decision with government monitoring only (equation 2) is lower than the reported revenue Y^{**} that satisfies the optimality condition once consumer monitoring is included (equation 4). The increase in reported revenue from Y^* to Y^{**} is driven by the reduction in the expected benefit of evasion. This reduction is due to the costs of collusion and to the fact that the detection probability might be higher if consumers can act as whistle-blowers. In this subsection, I describe two relevant mechanisms behind the effectiveness of a consumer monitoring program, which I investigate further in the empirical analysis.

Volume of consumers. The enforcement change introduced by consumer monitoring is

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rates or audit strategies are strictly confidential, it is not possible to distinguish in the data changes in audit rate from changes in detection ability conditional on audit. The conceptual distinction is useful, nonetheless, to illustrate how information from consumer monitoring can augment the effectiveness of government audits even if there are no changes in audit rates, which implies a higher risk of evasion faced by taxpayers.

[17] I assume that if the firm is audited the government will consider as tax evasion the amount not reported based on the posted price $\bar{y}$, not the discounted price. Therefore, $\bar{Y}$ will be the true revenue of the firm, instead of the revenue net of transfers to consumers.

stronger the larger the increase in the detection probability. Under whistle-blower threat, therefore, the increase in reported revenue is higher for firms that have a large number of consumers N. This comparative statics follows from the increase in detection probability induced by a higher risk of a whistle-blower. The increase in reported revenue should increase with the foot traffic' of the firm, or volume of consumers for a given firm size or true revenue $\bar{Y}$. Also, for a given 'foot traffic' the relative change of reported revenue should be smaller for larger firms. This distinction between firm size and volume of consumers is relevant to shed light on one of the specific mechanisms of third-party information: the enforcement effect may result from exposure to whistle-blower threats.

Value of rewards. In the framework described above, higher rewards to consumers should have stronger effects on compliance. In a collusive deal, firms try to match the rewards provided by the government through a discount. Therefore, the reward to consumers α directly reduces firms' benefits from evasion. In the empirical setting, the reward has a lottery component so the value of α for consumers may be actually higher than the monetary expected value of the program's reward. As I discuss in section 4.2, a taste for gambling or behavioral biases in assessing the odds of winning prizes could inflate the perceived value of lottery rewards, making it particularly costly for a firm to replicate α through a discount.

2 Institutional Background and Data

This section provides institutional background on the *Nota Fiscal Paulista* (NFP) policy, and the details of the program that are important for the empirical analysis. First, I briefly introduce the relevant features of the Brazilian tax system and the NFP policy. Then, I describe the datasets I use and sample definitions.[18]

2.1 Institutional Background

The State of Sao Paulo is the largest state in Brazil: it accounts for 34% of the country's GDP, and has a population of 42 million people. The metropolitan area of Sao Paulo is the second most populous in the Americas. The state of Sao Paulo depends mostly on

[18]Throughout the paper I will convert Brazilian Reais to dollars using US$1=R$2 exchange rate, which is the average exchange rate during the period of analysis (2004 – 2011).

its own tax revenue, as opposed to federal transfers.[19] States in Brazil have two main tax instruments: a tax on goods and certain services (ICMS) and a property tax on motor vehicles (IPVA).[20] The ICMS is a value added tax (VAT), and it is the most important source of revenue in Sao Paulo. Because the ICMS is a state-level tax in Brazil, its legislation and enforcement policies are determined by the states. The most common ICMS rate is 18% over the valued added.[21]

In 2007 the state of Sao Paulo collected U.S. $34.5 billion with the ICMS, equivalent to 7.6% of the state's GDP. Overall, tax revenue in Brazil is very high for developing country standards. Considering all taxes, tax revenue amounts to 34% of the country's GDP (IMF, 2011).[22] Nonetheless, there are many reasons to believe that tax compliance is not perfect in Brazil. According to La Porta and Shleifer (2014), estimates of size of the country's informal economy range from 19% to 34% of GDP. Unregistered firms are invisible to the tax authority, and no taxes are levied directly on them. Formal firms have to report their activity to the tax authority on a monthly basis, and pay the ICMS in relation to their reported activity. Despite the tax authority's monitoring, compliance by formal firms is also limited. In the World Business Environment Survey 2003, on average Brazilian formal firms claim that 20-30% of sales are not reported to the tax authority by a typical firm in their area of activity.[23] When the NFP program was implemented, the Secretary of

[19]When the NFP policy was implemented in 2007, Sao Paulo's own tax revenue was 75% of its total revenue according to the balance sheets of the Brazilian Treasury Department. Moreover, Luque et al. (2011) argue that Sao Paulo state generated more than 40% of the Federal tax revenue, while receiving less than 35% of Federal transfers in 2005. Federal taxes include, for instance, individual and corporate income taxes, payroll taxes and taxes on manufactured products.

[20]The IPVA ("Imposto sobre Propriedade de Veículos Automotores") and ICMS ("Imposto sobre Circulação de Mercadorias e Serviços") typically account for 95% of the total tax collected by states. The other two sources of tax revenue are a tax on bequests and donations called ITCMD ("Imposto sobre Transmissão Causa Mortis e Doações") and fees for public services.

[21]The value added is the total value of sales net of inputs. For the majority of goods, the ICMS rate is 18%. In some cases, a reduced rate of 7% or a higher rate 25% is applied. As is common in VAT across the world (Keen and Mintz, 2004), there is a threshold below which firms pay taxes over gross revenue instead of the value added. Firms that have yearly gross revenue of less than U.S. $1.2 million can choose to be in a simplified tax regime called SIMPLES in which firms pay taxes based on gross revenue. The ICMS average rate in the SIMPLES is 3.5% of gross revenue. For more details about SIMPLES see De Paula and Scheinkman (2010) or Monteiro and Assunção (2012).

[22]The average tax revenue as a share of GDP in developing countries is 17.6% (Gordon and Li, 2009).

[23]The question in Batra (2003) is: "Recognizing the difficulties many enterprises face in fully complying with taxes and regulations, what percentage of the total sales would you estimate a typical firm in your area of activity keeps off the books: 1 (none); 2(1-10%); 3 (11-20%); 4 (21-30%); 5 (31 - 40%); 6 (41 -50%); 7 (over 50%)." In the case of establishments that sell to final consumers, the tax evasion problem is likely to be more severe since firms are smaller than in upstream sectors. The percentage of sales that are underreported or not reported at all reaches 30-40% among smaller firms in Brazil.

Finance of Sao Paulo at the time argued that the retail sector in the state evaded taxes on approximately 60% of its sales (Jornal Estado de São Paulo, 2007).

2.2 The Nota Fiscal Paulista program

The *Nota Fiscal Paulista* (NFP) program was created by the government of the state of Sao Paulo in October 2007 in order to reduce tax evasion of the state's VAT, and to foster a culture of tax compliance.[24] The idea behind the NFP program is to use consumers as tax auditors by introducing targeted incentives for consumers to ensure that firms report final sales. The incentives provided by the program replicate the VAT self-enforcement already in place for business to business transactions; rewards are increasing in the value of the purchase such that buyer has incentives to ask for receipts, and to make sure that the value of the purchase is reported correctly by the supplier. Therefore, the NFP program directly affects two forms of under-reporting: (i) establishments may not report a transaction at all, or (ii) establishments may falsely claim a lower transaction value.[25]

In a nutshell, the program introduced the possibility of identifying an individual taxpayer number – hereinafter refereed to as Social Security Number (SSN) equivalents – on each receipt, and created a system of tax rebates and monthly lotteries so that final consumers have incentives to request receipts with their SSN. Since the process of reporting receipts to the tax authority is done by establishments, and the consumer's SSN is attached to it, consumers do not need to send their receipts to the tax authority to get the rewards, which markedly reduces consumer participation costs. Consumers have to create an online account at the tax authority's website, which allows them to collect rewards and cross-check the receipts issued with their SSNs. The online system also allows consumers to file complaints about specific firms, which introduces a threat that consumers may act as whistle-blowers.

Implementation. The reward system was introduced along with a system of transaction reporting through which firms were required to send electronically to the tax authority all receipts they issue - with or without a SSN. Previously, firms only reported monthly aggregated information and were required to keep all the supporting documents and receipts in their books. With the new system, firms were also required to send the govern-

[24]The NFP policy was framed as an incentive to improve tax morale. The official slogan of the policy was "Incentive Program for Fiscal Citizenship" ("Programa de Incentivo à Cidadania Fiscal").

[25]A common way to evade taxes in Brazil is to underreport the value of a sale. This type of evasion is informally known as "meia-nota" or "half-receipt" (Amaral et al, 2009).

ment individual sales information in a monthly basis.[26] Importantly, this new system did not change the technology of receipts issued by retail firms during the period of analysis (2004 -2011). Billing machines that issue receipts with time stamps and serial codes (called *Coupom Fiscal* in Brazil) were already widespread in Sao Paulo in the early 2000's, and billing machines with real time electronic transmission of receipts directly to the tax authority (called *Nota Fiscal de Consumidor Eletrônica* in Brazil) – that Eissa et. al. (2014) found to be effective to reduce tax evasion in Rwanda – only started being introduced in Sao Paulo in 2015. Therefore, the requirement to send disaggregated sales information alone – without incentives to consumers – should not change firm compliance behavior: firms could simply send to the tax authority information on individual transactions they were already reporting in their official books in the end of each month.[27]

Eligibility. The government leveraged the fact that SSNs are not considered sensitive information in Brazil.[28] Any person that holds a Brazilian SSN equivalent is eligible to participate in the program.[29] No pre-registration is needed for consumers to be eligible for tax rebates. In order to be rewarded with lottery tickets for monthly cash prizes, consumers must create an online account at the tax authority's website.

The reward system. At the moment of purchase, the consumer may ask for the receipt, and give the cashier her SSN. Establishments must send all receipts – with or without SSNs – to the tax authority on a monthly basis. As the tax authority receives the receipts, it creates an account for each SSN where it stores all receipt information and the tax rebates due from each receipt.[30] If the consumer has an online account and has opted in for lotteries, the system also automatically generates lottery tickets for every total of U.S. $50 spent. During the registration, a consumer may also opt to receive an email every time a receipt is issued with her SSN. The online account displays how much consumers

[26]The system is called TD-REDF ("Transmissor de Dados para o Registro Eletrônico de Documento Fiscal" or "Data Transmitter for Electronic Registration of Fiscal Document").

[27]In addition, during the period of analysis product codes and bar codes were not standardized so the itemized information was not used beyond the total value reported in each receipt that was used to calculate the rewards.

[28]For instance, the Brazilian SSN equivalent (CPF) is written on checks under the signature line, and consumers are frequently asked for their CPF in business transactions. Also, Brazilians have multiple identification numbers that make identity theft more costly: individual identification, taxpayer number, a voter identification, a social security identification, among others.

[29]Throughout the paper I will refer to the CPF ("Cadastro de Pessoa Física") as SSN. I will focus on CPF holders only. They are the overwhelming majority of participants in the program. Some NFP participants have a CNPJ ("Cadastro Nacional de Pessoa Jurídica"), which is a SSN for firms. Charitable institutions and condominiums also have CNPJ and receive the exact same benefits as final consumers.

[30]Throughout the paper I will refer to the receipts with SSN as 'NFP receipts'.

are rewarded for each transaction, and has tabs where a consumer can click to manage rewards and file complaints. Figure 1a shows an online account example, and Figure 1b displays a receipt with a consumer's SSN.[31]

Tax rebates. For a given receipt, consumers receive a tax rebate of 30% of the VAT paid by the final sale establishment in a month – i.e., it is only a share of the value added downstream, not the entire value added tax –, shared among all consumers of that establishment who provided their SSN that month in proportion to their expenditure in that establishment and month. The calculation of the benefit, thus, is a function of an entire month's worth of SSN receipts and resultant tax paid by the final sales establishment.[32] On average, the tax rebate is 0.8% of the total value of the purchase. The rebate value is consistent with the fact that sales to final consumers account for less than 15% of the value added.

Lotteries. NFP has held monthly lotteries since December 2008. For every U.S. $50 a consumer spends in NFP receipts per month, she receives one lottery ticket.[33] If the consumer opts in for these lotteries while enrolling online, lottery tickets are automatically generated based on the consumer's total expenditures in NFP receipts.[34] Lotteries are held around the 15th of each month, and each month 1.5 million prizes are distributed on average. Most prizes range from U.S. $5 to U.S. $25, and there are usually three large prizes from U.S. $15,000 to U.S. $500,000. On average, the expected value of the a lottery ticket is 0.2% of the total purchase.

Collecting rewards. Rewards can be: (i) direct deposited into the consumer's bank account, (ii) used to pay other state taxes, (iii) transferred to another person with an online

[31] The snapshot of the online account and the receipt in figures 1a and 1b are the author's own online account.

[32] If two consumers buy the same total value in the same shop and month they will receive the same tax rebate even if they bought different goods that may be taxed differently. This is partially due to the fact that the tax authority can only use the total value of the receipt to calculate the rebate shares of each individual since the itemized information in the receipt was not standardized in the period of analysis. More precisely, if the firm has N consumers in a month, the benefit consumer i receives from an NFP receipt depends directly on the total ICMS collected from establishment e in month m ($ICMS_{em}^{total}$), the total value of NFP purchases associated with consumer i and establishment e in month m (V_{iem}) and inversely on the total value of NFP purchases in establishment e in month m ($\sum_{j=1}^{N} V_{jem}$). Also, there is a cap on how much an individual consumer can receive: 7.5% of the total expenditure, which is 30% of the highest VAT rate (of 25%). Thus, $TaxRebate_{ime} = \min\{0.3 \cdot [ICMS_{em}^{total} \times \frac{V_{iem}}{\sum_{j=1}^{N} V_{jem}}], 0.075 \cdot V_{ime}\}$.

[33] The lottery draw in month m uses lottery tickets generated in month $m-4$.This 4-month gap is necessary in order to make sure that all disputes over missing or incorrect receipts are resolved before the lottery.

[34] Therefore, 50 receipts of 1 dollar value, and 1 receipt of 50 dollar value are equivalent, and generate 1 lottery ticket.

account or to a charity. Consumers must have an online account to manage the rewards. Tax rebates are disbursed biannually. In April, tax rebates from July to December of the previous year are made available to consumers; in October the tax authority disburses tax rebates from purchases between January and June of the same year. Lottery prizes can be collected soon after the results are released. Consumers have up to five years to claim the benefits.

Complaints. Consumers may file complaints regarding a purchase made at a specific establishment up to the 15th of the month following the purchase. The consumer must identify the establishment and select a reason for the complaint from a 5-option menu: (i) the establishment did not issue a receipt; (ii) the establishment refused to write the consumer's SSN on the receipt; (iii) the establishment issued the receipt but did not register it electronically; (iv) there is a discrepancy between the information on the receipt issued to the consumer and the receipt registered electronically at the tax authority; and (v) other reasons.[35] Consumers receive a part of the fines paid by the firm as rewards instead of the usual monetary reward when they file a complaint that escalates to a fine. I do not observe, however, the consequences of a given complaint. In the empirical analysis, I therefore use all complaints.

Fines. Establishments that do not issue the NFP receipt correctly are subject to penalties and potentially more comprehensive audits by the tax authority. Under tax law, establishments can pay up to 100% of the evaded tax, and there are additional penalties for for misreporting documents and receipts.[36] If a firm issues a receipt with an individual SSN and misreports the transaction, the process of punishing firms is straightforward if the consumer has a SSN receipt as proof of purchase. [37] In this case, there are fines applied by the consumer's protection bureau PROCON (Fundação de Proteção e Defesa do Consumidor).

Timeline. NFP was implemented in the retail sector between October 2007 and Decem-

[35]At that point the consumer does not need to provide evidence to support her complaint, and she can describe details of her case in a text box. The establishment is notified that a complaint was filed via email or letter, and it has 10 days to respond to the complaint. If the consumer is not satisfied with the response, she can file an official complaint. Before this point, the tax authority is not involved in the case. If the consumer decides to file an official complaint, she has to submit supporting evidence by scanning or taking a picture of the receipt or any other proof of purchase. From that point onward, the tax authority and the Consumer Protection Bureau will review the case and apply fines accordingly.

[36]For the legislation on tax penalties *Part IV "violations concerning fiscal documents and tax forms"* of Decree 45490/00.

[37]Dyck, Morse and Zingales (2010) find that, in the context of U.S. corporate fraud, access to information and monetary rewards play an important role in encouraging whistle-blowing.

ber 2008. The tax rebate system and electronic submission of receipts was phased-in by groups of sectors between October 2007 and May 2008. The online system to file complaints was available starting in October 2008; the first lottery occurred in December 2008. In April 2009, the tax authority disbursed tax rebates for the first time from all purchases since October 2007, and every 6-months thereafter the government disbursed tax rebates according to the schedule described above.[38]

Figure 2 shows the time series of the total number of receipts reported to the tax authority from the beginning of the program until the end of 2011. The three vertical lines indicate the beginning of phase-in, the end of phase-in, and the first lottery in December 2008. The purpose of the figure is to show the mechanical increase in the total number of receipts reported electronically by establishments to the tax authority as the program was being implemented. After May 2008, the total number of receipts submitted to the tax authority follows the seasonality of consumption.

During the period of analysis from October 2007 to December 2011, 13 million people enrolled online at the tax authority's website, which is 40% of the people ages 15 and above in the state. In a given month there are typically 5 million more people asking for SSN receipts than there are online accounts. This gap highlights that the cost to start participating in the program is relatively small: no pre-registration is needed since one just needs to have a social security number; but enrolling online might be more costly. Over 40 million people asked for SSN receipts more than once.[39] Over U.S. $1.1 billion has been distributed in tax rebates and lottery prizes. 740,000 establishments have submitted over 3.5 billion receipts with consumers' SSNs to the tax authority. During the period of analysis there was a total of 1,151,518 complaints sent to the tax authority by 135,102 different consumers regarding 134,054 different establishments to the tax authority during the period of analysis.

2.3 Data and Sample Definition

In this section, I briefly describe each data source, and the summary statistics of the data. First, I present the establishment-level data and the main outcomes I examine in section 3.

[38] Even though the NFP program is targeted at final consumer sales, consumers who purchased directly from wholesalers and manufacturers could enjoy the same reward benefits as in retail purchases.

[39] Since any SSN holder in Brazil is eligible for the rewards, people in neighboring states may also participate (the total population of Sao Paulo is 42 million). Over 500,000 consumers with online accounts are from municipalities outside the state of Sao Paulo.

Second, I explain the datasets at the consumer level, and the key variables I use in section 4.2. In both cases, I focus on features of the data most relevant for my empirical analysis. Additional details on variable definitions and sample choices can be found in the Online Appendix A.

2.3.1 Establishment Data

I use administrative data on establishment-level tax returns and registry information from the Department of Finance of the state of Sao Paulo, Brazil from January 2004 to December 2011.[40]

Reported revenue. The NFP program aims to ensure that firms accurately report final sales. Accordingly, the gross revenue reported by an establishment is the key variable directly affected by NFP. Therefore this variable is the primary outcome in my empirical analysis of establishment compliance. All establishments must report their gross revenue to the tax authority on a monthly basis. For more details on the specific forms used to construct this variable, see the Online Appendix A. In order to reduce the influence of outliers, I winsorize reported revenue by its 99^{th} percentile value.[41]

Reported revenue will be the main outcome throughout the paper. The amount of taxes paid by establishments has important measurement problems. For instance, it is affected by changes in tax payment rules or by changes in the tax forms. These types of changes generate mechanical increases and decreases in the time series of tax payments, even though the total tax liability of a establishment may not change. Importantly, in some cases, there is not a one-to-one relationship between an establishment's tax liability and how much it remits to the tax authority, due to tax withholding policies. In order to investigate the impact of NFP directly on total tax collection, I perform two exercises. First, I look at total tax take in Sao Paulo – irrespective of which sector and firm – and compare with total tax take for the rest of Brazil leaving Sao Paulo out (Figure 4b). Second, in the Online Appendix C Table C.2, I show results from running the main specification from section 3 in a subset of firms that are in sectors with close to no tax withholding through-

[40]Due to confidentiality reasons, I do not have access to data on audits rate or any information uncovered from audits. In addition, the data were de-identified, and no establishment data were provided from sectors that have fewer than five establishments, or from sectors in which one establishment is responsible for over 90% of the sector's tax revenue of that sector. In the groups of sectors I analyze – retail and wholesale – only 126 establishments were excluded from a total of 1,035,933 establishments registered in Sao Paulo over the period of analysis.

[41]I replace all values above 99th percentile of the reported revenue distribution by the 99th percentile value.

out the period of analysis to mitigate this measurement problem. For this subsample, I find that the effects on reported revenue are similar to the effects on taxes paid.

Establishment characteristics. From the registry of firms of Sao Paulo, the main variable I use is the establishment sector of activity. Sectors are defined according to a 7-digit code of the Brazilian National Classification of Economic Activity (CNAE version 2.1). The retail sectors are all the sectors that start with 47 plus motor vehicle retail under sectors that start with 45. Wholesale is defined by all sectors that start with 46, plus motor vehicle wholesale under sectors that start with 45. The sector definition is very detailed; for instance, 472 is Retail food, beverages, tobacco; 4722-9 is Retail meat and fish; and 4722-9/01 is Retail meat (butchery). Throughout the paper, *sector* refers to the 7-digit definition, unless otherwise noted.

Establishment sample. From the total of 1,283,777 unique establishments registered in Sao Paulo in the period of analysis,[42] I restrict attention to the 632,751 establishments classified as retail or wholesale – as described in the previous section . The final panel has approximately 20 million observations between January 2004 and December 2011.

Sector sample. I aggregate the reported revenue of the *establishment sample* by 7-digit sectors of activity between January 2004 and December 2011. There are 210 sectors: 90 in retail and 120 in wholesale. The sector sample has 24,990 observations. As a robustness check for the aggregate results, I also consider the two alternative samples described above.

Table 1a describes the *establishment*, *sector* and *employment* samples. Statistics for the *establishment sample* include the monthly gross reported revenue by establishment for the key groups I use in the empirical analysis. On average, over 40% of receipts reported by the establishments in the sample have SSNs attached to them.[43] Statistics for the *sector sample* display the average reported revenue across 7-digit retail and wholesale sectors I analyzed in section 3. The *employment sample* aggregates the annual employer-employee data by 5-digit sector, and the table shows the average number of formal employees per establishment for retail sectors registered in Sao Paulo, as well as in the other 26 states in Brazil.

[42] I exclude all establishments that report zero revenue across all months between January 2004 and December 2011

[43] As I explain in the next section, the data from the NFP program available to this project starts in January 2009. Therefore, establishment-level datasets generated from the program are not available before that.

2.3.2 Consumer Data

Consumer-level datasets are based on de-identified administrative data from NFP receipts and from online account activity at the tax authority's website.[44] Here I describe the datasets I use in section 3. Importantly, the consumer-level data are provided by the NFP program. Therefore, there is no "pre-NFP" data on receipts, or any other individual characteristic.[45]

Receipts data. This data file captures purchases for which final consumers asked for SSN receipts between January 2009 and December 2011. For these receipts the data include: month and year it was issued, the total amount spent, and an establishment identifier. The receipt dataset has information for all consumers that have made purchases with their SSN, even before they enrolled online.

The main variables I derive from the receipts dataset are: (i) *number of receipts*: the total number of SSN-identified receipts for which a consumer asks per month; (ii) *number of establishments*: the number of different establishments for which a consumer asks for SSN-identified receipts per month; (iii) *total expenditures with a SSN*: the total amount of money spent associated with the SSN-identified receipts, aggregated by consumer, per month; (iv) *average receipt value*: the average value among all purchases represented by a consumer's SSN-identified receipts in a given month. In order to reduce the influence of outliers I winsorize the *number of receipts* and *total expenditure in SSN receipts* by their 99^{th} percentile value.

Online account data. This dataset contains information on month and year of enrollment, the timing of monetary reward collection, and the amount received by 13 million individuals who created an online account at the tax authority's website from October 2007 to December 2011.[46] Additionally, the dataset contains participation in monthly lotteries: the total number of tickets each consumer held and the associated prizes she received.

[44] For confidentiality reasons, no information that may identify individuals was available to this study. A "fake" unique identifier was created for each individual SSN, and no information on names or addresses was provided. Also, for a given receipt, the total amount spent is rounded to the nearest integer, and the final data contains no information on prices or products that were purchased.

[45] The state tax authority has no information on individual income tax records or any other federal tax data. Apart from motor vehicle property information, state tax authorities do not usually collect data on individuals.

[46] All data on approximately 90 consumers who won one of the top 3 lottery prizes of over U.S. $500 were excluded from the datasets available to this study for confidentiality reasons. See Online Appendix A for more details.

The main variables derived from the online account dataset are: (i) *total amount claimed*: the total value of rewards claimed by consumers through bank account deposits; (ii) *number of lottery tickets*: the total number of lottery tickets a consumer holds per month; (iii) and *lottery prizes*: the number of lottery prizes and the value of lottery prizes per month.

Consumer sample. I take a 10% random sample of consumers who enrolled online by the end of 2011 – around 1.3 million people – and I construct a balanced monthly panel from the *receipts data* of consumer's participation in the program containing 46,505,268 observations between January 2009 and December 2011. Table 1b displays descriptive statistics of the *consumer sample*.

Lottery sample. This sample covers consumers who participated in one of the twelve monthly lotteries between June 2010 and May 2011. I restrict attention to consumers holding fewer than 40 lottery tickets per lottery, which is relevant to assure common support between lottery winners and non-winners in the event-study analysis I describe in section 4.2.[47] I merge the data on lottery ticket holdings and lottery prizes from this sample with the *receipts data*. The combined dataset of lotteries and receipts covers the time period between January 2010 and November 2011, i.e., 6 months before and after the first and last lottery considered in this analysis.

The second panel of Table 1b displays the descriptive statistics of the *lottery sample*. Since consumers need to be enrolled online in order to be eligible for lotteries, and since they must ask at for least U.S. $50 in SSN receipts to get one lottery ticket, consumers in the lottery sample have much higher participation rates than the consumers in the *consumer sample*.

3 The effect of third-party information trails on establishment compliance

To investigate the degree to which the availability of third-party information trails introduced by consumer rewards for requesting receipts can improve firm compliance, I begin by exploiting the impact of the introduction of the NFP program on revenue reported by establishments using a difference-in-differences (DD) research design.

The identification strategy exploits variation in treatment intensity from the policy change. I compare sectors two downstream sectors affected differently by the consumer

[47] See the Online Appendix A for a more detailed description of the *lottery sample*.

monitoring program: retail and wholesale. NFP targets final consumer sales, so establishments that sell mostly to final consumers are more affected than establishments selling mostly to other establishments. To exploit this difference I compare "treated" retail sectors to "control" wholesale sectors. I use a DD design to estimate changes in reported revenue by establishments in each group before and after the implementation of the program.

One advantage of the data is that I have a long time series of pre-NFP observations of reported revenue changes in the sector groups. Thus, I can shed light on whether a key identification assumption in a DD holds: that trends in potential reported revenue changes are parallel for retail and wholesale sectors. Figure 3a displays changes in total raw reported revenue by group of sectors from January 2005 to December 2011. In this figure, each data point is scaled by the average monthly reported revenue before the introduction of the NFP in October 2007 for the group.

In Figure 3a, retail and wholesale reported revenue changes closely trace each other until program implementation. The vertical lines highlight the key moments in the implementation of the program discussed in section 2.2. Following implementation, change in reported revenue gradually increases in retail sectors, relative to wholesale sectors. This gradual change is consistent with the fact that the program was not implemented at once, and consumer participation increased steadily over time. Since the figure displays raw data, there is quite a bit of variation across months of the year due to the seasonality of consumption. In particular, in retail sectors, reported revenue spikes each December, consistent with increased holiday-related consumption.

In order to measure the effect of the program across time, I run a flexible DD specification that includes 17 time dummies for 6-month windows from 2004 - 2011, using October 2007 (the starting point of the program's implementation) as a reference point. Each 6-month window, denoted by k, is associated with a dummy variable $Period_t^k$, which equals one if time period t falls within window k: [48]

$$lnR_{st} = \eta_s + \gamma_t + \sum_{k=-8}^{8} \beta^k (Treat_s \cdot Period_t^k) + u_{st} \tag{5}$$

where lnR_{st} is the log of reported revenue in sector s and time t; η_s are 7-digit sector fixed effects and γ_t are dummies for each month of each year. $Treat_s = 1$ if sector s is

[48]For instance, $Period_t^0 = 1$ if $t \in [Oct.07, Mar.08]$, $Period_t^{-1} = 1$ if $t \in [Apr.07, Sep.07]$, and $Period_t^1 = 1$ if $t \in [Apr.08, Sep.08]$.

a retail sector, and u_{st} is clustered by sector. This specification allows me to show the treatment effect across time, while controlling for finely-defined time and sector effects.

Figure 3b plots the coefficients and the 95% confidence intervals from estimating equation (5) without a constant. The difference between the two groups is relatively constant before NFP. By the time the program is fully implemented – after the second dashed line – the difference in log reported revenue between the two groups begins to grow. This effect, averaged across all post-implementation periods, can be estimated from a standard DD specification:

$$lnR_{st} = \eta_s + \gamma_t + \beta Treat_s \cdot Post_t + u_{st} \tag{6}$$

where $Post_t = 1$ if $t \geq October$ 2007 and u_{st} is clustered by sector. Estimates of equation (6) suggest that the NFP program induced a positive and significant 22% increase in reported revenue by establishments across the 4-year period following implementation. Because I am exploiting differences in the treatment intensity across establishments, the estimated effect is a lower bound of the program's impact. The control group was also potentially affected by the policy: either directly from sales to final consumers or indirectly from the self-enforcing properties of the VAT.

I conduct a number of robustness checks reported in the Online Appendix C. The results are robust to winsorizing the top 5% or the top 0.1%, as well as to winsorizing within-year ranks of firm revenue instead of top 1% in the overall distribution to deal with the influence of outliers. I also use an alternative sample of establishments already operating by January 2004 and that were still active the quarter before NFP implementation to restrict attention to establishments that were created at least three years before the program started. Additionally, I show that the firms in the excluded sectors upstream behaved similarly to wholesale, which is consistent with the argument that firms that do more business to business transactions should be affected less by this policy.

To make sure that the retail-wholesale comparison is indeed capturing an increase in compliance, rather than an increase in actual revenue, I use tertiary sector annual survey from the Brazilian Census Bureau (IBGE).[49] Two steps are taken to ensure that the survey elicits accurate information on establishments' activities. First, micro-level data are kept confidential. Second, Brazilian law ensures that no information reported in this survey

[49]PAC ("Pesquisa anual do comércio") is an annual national survey conducted by IBGE based on a sample of formal establishments in Brazil. The retail-wholesale revenue ratio was calculated from aggregate tables of the survey. The micro-data is confidential.

can be used as evidence in a legal proceeding against an establishment. By comparing two independent sources of information on establishments' reported revenue – administrative data from Sao Paulo and the census data – I can address two alternative explanations for the differential change in reported revenue between retail and wholesale: *(i)* a nationwide differential change in the revenue ratio between the two groups;[50] *(ii)* an actual increase in retail revenue in Sao Paulo, relative to wholesale.

Figure 4a compares changes in the revenue ratio of retail to wholesale, $r \equiv \frac{\text{retail revenue}}{\text{wholesale revenue}}$, from the Sao Paulo administrative data to changes in the same ratio from the census survey.[51] Each data point is scaled by the ratio r in 2004. Until the introduction of NFP in 2007, the three ratios follow similar time trends. After 2007, the ratio derived from reported revenue in Sao Paulo tax data increase, whereas the ratios derived from survey data – in Sao Paulo state and nationwide – remain relatively unchanged. This is inconsistent with the notion that changes in reported revenue in Sao Paulo tax data are due to an increase in actual revenue in retail relative to wholesale sectors, or by a nationwide change.

Figure 4b compares changes in the total tax take in Sao Paulo as a share of GDP compared to all other states combined relatively leaving Sao Paulo out. The figure shows a slight level shift in tax/GDP in Sao Paulo of 3.5% on average in total tax take relatively to the rest of the country after 2007. This increase is consistent with 22% effect in retail as taxes from final consumer sales are less than 15% of the total value added.

In the Online Appendix section D.1 I study real responses to the policy by analyzing formal employment or exit decision of firms. The evidence indicates that the increase in tax enforcement did not affect these outcomes during the period of analysis. The null effect may indicate that the implied increase in the effective tax rate is not large enough to affect the firm along these margins, and may just reduce evasion rents. The lack of real responses is consistent with the increase in reported revenue being a reporting effect, rather than an actual increase in sales, in which case I could potentially observe an increase in employment or a drop in exit.

[50] The time period post-NFP overlaps with the great recession in the U.S. that could have potentially affected retail and wholesale sectors differently. Therefore, the fact that the revenue ratio from the nationwide survey data is constant is an important indication that the difference in reported revenue between retail and wholesale after NFP implementation from Figure 3a is indeed a compliance effect.

[51] The national ratio is based on the total gross revenue from sales ("Receita Bruta de Venda"). Retail revenue includes the retail and motor-vehicle trade. Because the national data adds up all revenue within both groups of sectors, in this graph I consider all reported revenue in each group of sector from administrative data from Sao Paulo, instead of the reported revenue from the *establishment sample*.

4 Mechanisms: whistle-blower threats and consumer rewards

In order to investigate the mechanisms through which the government can credibly harness the information consumers have on firms' evasion to improve enforcement, I turn to the micro data on establishments, receipts, and consumers following the predictions from the conceptual framework in section 1. First, I study the role of whistle-blower threats by examining heterogeneous effects of the program, and by analyzing the behavior of firms after consumers blow the whistle. Second, I investigate the role of consumer rewards and discuss how behavioral biases may amplify individual responses to rewards and make it more costly for firms to match the government incentives in a collusive deal.

4.1 Whistle-blowers

Whistle-blower threats. I examine the effect of heterogeneity in the responses of establishments to the NFP policy in order to shed light on the role of whistle-blower threats discussed in section 1. I use the *volume of transactions* to capture the increased threat of audit under consumer monitoring: the larger the number of consumers the more likely it may be that one of those consumers will blow the whistle when the firm evades taxes. Therefore, the effect of the program should be increasing in the volume of transactions.

To define the *volume of transactions* I count the number of receipts per establishment from the *receipts data*, and I rank retail sectors by the average number of transaction per establishment.[52]

$$lnR_{its} = \eta_i + \gamma_t + \sum_{m=1}^{k} \alpha_m (d_{ms}.DD_{ts}) + f(x_i)^* DD_{ts} + \varepsilon_{its} \tag{7}$$

where lnR_{its} is the log of reported revenue where in establishment i in period t and sector s,. Establishment fixed effects are denoted by η_i, γ_t is a month-year fixed effect. The term $f(x_i)$ is a 3rd-order polynomial of establishment size as measured by the average reported revenue three years before the program, and DD_{ts} variable is defined by the interaction between a dummy for retail sectors and a dummy that equals 1 for time periods after October 2007. The error ε_{its} is clustered by sector. The term $d_{ms} = 1$ if sector s is in quintile k of the transaction volume distribution across sectors instead of the receipt value

[52]Examples of sectors classified as having low volume of transactions: art supplies and second hand shops. Examples of sectors classified as having high volume of transactions: supermarkets and gas stations.

distribution. I flexibly control for establishment size effect through an interaction of DD_{ts} with $f(x_i)$ to separate the size effect from the effect of volume of consumers as discussed in the conceptual framework.

The establishment-level regression is run in a two-period DD, for which the data is collapsed by *pre* and *post*. The *pre* period is between January 2004 and September 2007, and the *post* period is between October 2007 and December 2011. This precaution helps to ignore serial correlation when computing standard errors (Bertrand, Duflo, and Mullainathan, 2004). The regressions are dollar-weighted – i.e., each observation is weighted by its pre-NFP value – such that each observation contributes to all regression estimates according to its economic scale to best approximate the sector aggregate-level analysis.[53]

Figure 5 plots the coefficients and 95% confidence interval from the estimating equation (7). The figure suggests that there is a monotonic increasing relationship between the transaction volume quintiles and the effect of the program: the effect of the program is stronger in sectors with a high volume of transactions. This pattern is consistent with the prediction described in section 1.2. The results are similar if I examine heterogeneity by transaction value allowing for differential effects by firm size. The compliance effect is concentrated among small transaction values, which should be associated with a higher volume of transactions all else equal.

Table 2 shows regression results of specifications similar to equation (7). Column (1) shows the simple DD coefficient for the full sample, and column (2) restricts attention to establishments that were already active in January 2004. The results are very similar in both samples, and are also similar to the aggregate result discussed in the previous section. In Column (3) I look at heterogeneity in the DD coefficient if a establishment is in a sector above or below median volume of transactions controlling for differential effects according to a 3rd order polynomial of pre-treatment firm size. The results simply reflect the patterns already observed in Figure 5. Column (4) shows heterogeneity in the DD coefficient according to weather a establishment is below or above the median pre-program size distribution, controlling for differential effects by volume of transactions. The results suggest that the effect of the program is relatively stronger for smaller firms,

[53] I find qualitatively similar results with attenuated magnitudes relative to the aggregate results when not dollar weighting because of the relatively high weight placed firms that collectively generate very little revenue. Similarly to the average effect, the heterogeneous results are robust to winsorizing the dependent variable at different cutoffs (0.1% and 5% instead of 1%) and different sample choices as described in the Online Appendix C. Standard errors are also robust to clustering at the establishment or time level instead of sector.

which is consistent with a higher baseline compliance among larger firms.

The results speak to a broader theory that information trails can have an enforcement effect through whistle-blower threats (Kleven, Kreiner and Saez, 2015). Kleven (2014) argues that derivative information makes full evasion infeasible even when there is no systematic third-party reporting. This program is changing the availability of information trails, and the threat imposed by potential whistle-blowers might help to explain how this program can work despite collusion opportunities between the buyer and the seller.

Whistle-blower event study. The evidence above indicates that whistle-blower threats could be an important device to improve compliance. In order to further examine how whistle-blowers affect firm behavior, I exploit a direct link between the participation of consumers in the enforcement effort and firm behavior. I use a dataset with over 1 million complaints to analyze how firms respond after a consumer blows the whistle. Once a firm receives a consumer complaint, it may increase the perceived detection probability due to whistle-blower threats.

Every month, a firm may receive a complaint from a consumer through the NFP website. A firm is typically notified by a complaint up to one month after the purchase. In order to study the effect of consumers' complaints I examine the impact of the first complaint a firm gets from a consumer through the website in Figure 1a. Different firms received their first complaints at different points in time, and I can exploit the timing of the first complaint to assess the response of firms. The likelihood of receiving a complaint in a given point in time, however, may be driven by the volume of sales leading up to the first complaint. It is possible that firms that have a large volume of sales in a given month may be followed by a lower reported revenue in the next period due to mean reversion or other seasonal characteristics. Therefore, exploiting the timing of the complaint alone might not be ideal, as subsequent changes in reporting patterns after the first complaint might reflect real changes in economic activity of the firm.

In order to circumvent mean-reversion and other seasonal effects, I build a counterfactual for each complaint event. Following Hilger (2014) I create an "event-control" group composed of firms that did not receive their first complaints by a given date. I use a subset of the establishment sample defined in section 2.3 I consider only retail firms, and within retail I only retain the firms that did not exit before 2009. The data is monthly between June 2009 and May 2011. Throughout this period, 134,054 or 25% of establishments received at least one complaint. I use a re-weighting method based on quartiles of the propensity score of getting a complaint in a given period to control for firm characteristics and past outcomes.[54]

Let $g \in \{T, C\}$ index each firm as "complaint" T or a "no-complaint" C in a given month. Let t_O index the month in which an outcome is observed, and t_E index the month in which a consumer blows the whistle on the firm for the first time (the "event-month"). Define $k \equiv t_O - t_E$ as the number of "periods" or months after/before the first complaint. I performed this re-weighting exercise separately for each month between June 2009 and May 2011, and I collapsed the data by event-month $k, k \in [-6, 6]$, using the propensity score weights.

Figure 6a displays changes in the total number of transactions *complaint* and *no-complaint* firms report to the tax authority and $k \in [-6, 6]$, and figure 6b shows changes in reported revenue relative to 6 months before the first consumer blows the whistle. The x-axis shows the distance in months to the first complaint or "event-month." The graph displays the estimated DD coefficient from estimating the following equation on the collapsed data for $k \in [-6, 6]$:

$$lnY_{gj} = \gamma_j + \pi_g + \beta \cdot I\{j \geq 0, g = T\} + u_{gj}, \tag{8}$$

where lnY_{gj} is either the log of the number of receipts group g reports to the government in "event-month" j or the log of reported revenue in "event-month" j. The graph displays the estimated DD coefficient from estimating equation 8 on the collapsed data for $k \in [-6, 6]$. I find a significant 14% increase in the number of receipts establishments issue and a 6% increase in reported revenue over 13 months. The impact of the first complaint is capturing the overall impact of complaints, as some firms received additional complaints after time zero. It can be interpreted as an increase in the perceived detection probability as firms learn that governments have more information about their non-compliance. Audit probabilities could change as a result, but even if audit rates do not change, firms could perceive a higher risk of getting caught as the government is better informed.

Together, the impact of consumers blowing the whistle and the heterogeneous effect of the consumer-monitoring based on whistle-blower threats is consistent with the argument that whistle-blowers can be an important part of the explanation for why third-party

[54]The propensity score of a firm receiving its first complaint at a given time is estimated using time specific trends for each sector, age of the firm, number of establishments by firm, dummy for establishment-headquarter, dummies for legal nature of the firm, sector and time fixed effects, dummy for location in the metropolitan region of Sao Paulo, and the three lags of third-order polynomials of reported revenue, reported receipts, SSN receipts and number of consumers. For a detailed description of the propensity score and reweighting see the Online Appendix B1.

reporting is so effective to ensure compliance. In the context of NFP, it can be a tool for the government to tap into the wealth of information that consumers elicit when asking for receipts from hard-to-tax firms that self report final sales.

4.2 Consumer responses to lottery rewards

As discussed in the conceptual framework, the more that consumers value rewards, the more firms need to compensate consumers in a collusive deal, which will increase the effectiveness of consumer monitoring. First, I provide evidence that the program is salient by exploiting variation in the disbursement schedules of the monetary rewards. Then, I exploit variation from the monthly lotteries to investigate whether potential behavioral biases with respect to lotteries may amplify the response consumers have from rewards.

Are consumers paying attention to the rewards? I show that consumers are paying attention to the schedule of lottery prizes and tax rebate disbursements. First, I verify that the release of monthly lottery results is salient to consumers by examining changes in the volume of Google searches about NFP. Google data aggregates information from millions of searches, and they can meaningfully capture salient social patterns that other survey methods cannot capture as easily (Stephens-Davidowitz, 2014).[55] Around the 15th of each month, the tax authority performs the lottery draws and releases information on lottery winners. A consumer can only check her lottery results by logging in to her online account at the tax authority's website. The actual address is not straightforward to remember (http://www.nfp.fazenda.sp.gov.br); as a result, consumers looking for this address may search for the program's name or initials.

Figure 7a pools Google search data from the first to the last day of each month between 2008-2011, and it scales each data point by the first day of the month.[56] From the figure, it is clear that there is an increase in search volume around the time the tax authority releases the results of the lotteries: it is 16% higher than on the first day of the month. The gray line displays data from searches with the word "futebol" (soccer in Portuguese) which provides a metric of how the general volume of Google searches varies within a month.

[55]Hoopes et. al. (2014) use Google and Wikipedia searches about U.S. income tax to show that the propensity to search varies systematically with tax salience.

[56]I exclude the months of April and October – during which the government disburses the tax rebates – to make sure that the search pattern is related to the lotteries. Including these two months does not change the pattern in the graph.

Second, I examine whether consumers are paying attention to the tax rebate schedule of the program. As described in the previous section, the tax authority disburses tax rebates biannually. Figure 7b shows that the timing of disbursement is salient: the total amount of rewards requested for bank account deposits spike as soon as tax rebates become available every April and October.[57]

The lottery effect. As detailed in section 1.2, the more consumers value the rewards α, the more effective NFP will be in preventing tax evasion.

The lottery component of the rewards may leverage consumers' taste for gambling or individual behavioral biases. Friedman and Savage (1948) noted that many governments consider lotteries an effective way to raise revenue as individuals may be willing to pay for lotteries paying a negative expected value. Filiz-Ozbay et al. (2013) find evidence that prize-linked savings offered by commercial banks and governments around the world may be more effective at increasing savings than regular interest payments with the same expected value.

In addition, the NFP monthly lotteries typically have three very large prizes – the top prize can be as large as U.S. $500,000 – and millions ofsmall prizes, which is a payoff structure commonly seen in gambling games and prize-linked savings accounts (Guillen and Tschoegl, 2002). The skewness of the prize values may be a tool to create salience. Bordalo et al. (2013) argue that when comparing alternative risky lotteries, individuals pay attention to the payoffs that are most different relative to their objective probabilities. If consumers exhibit behavioral biases with respect to the NFP lotteries, it would be more difficult for firms to try and replicate the government's rewards to avoid truthfully reporting sales.

I first focus on the random variation in lottery wins to document consumer behavioral responses to lottery rewards. Consumers may use past wins as a signal of their likelihood of getting a lottery prize, which would be consistent with misperception of randomness and the use of heuristics in making choices under uncertainty. Guryan and Kearney (2008) find that consumers increased their estimate of the probability a ticket bought from the store that sold a winning ticket in the past would be a lottery winner (the "lucky store effect").[58]

[57] Consumers can use rewards in other ways – e.g., they can be transferred to a third party, used to pay other taxes or saved for a later deposit – so the total amount in the graph will not necessarily add up to the total amount available to consumers at that point in time.

[58] They argue that consumers may rationalize the observed streaks by inferring heterogeneity in the data generating process. In the context of financial investments, Kaustia and Knüpfer (2008) find evidence of

To analyze the effect of lotteries I create a natural "event-control" group composed of people that held the same number of lottery tickets in a given lottery butdid not win prizes. I use the lottery sample defined in section 2.3.2: all consumers that participated in monthly lotteries between June 2010 and May 2011. Each of the 12 monthly lotteries had 1.5 million lottery prizes and over 50 million lottery tickets. There are typically 1,407,394 prizes of U.S. $5, 76,303 prizes of U.S. $10, 15,000 prizes of U.S. $25, 1,000 prizes of U.S. $125, and 300 prizes of U.S. $500. Because it is common for individuals to hold more than one lottery ticket in a given month, there are many cases of consumers that received a total of U.S. $15, U.S. $20, U.S. $30, U.S. $35, by winning more than one prize.

Let $g \in \{T, C\}$ index each consumer as "winners" T or a "non-winners" C in a given month. I use a re-weighting method based on DiNardo, Fortin, and Lemieux (1996) to flexibly control for the number of lottery tickets individuals hold. I create bins for each possible number of lottery ticket holdings up to 40 tickets, which is the set of lottery tickets for which there is common support between the two groups.[59] I then re-weight the non-winners group such that each bin carries the same relative weight as the analogous bin in the winner group distribution across lottery ticket holdings. This method ensures that I use the random component of the lottery by matching the two groups based on the odds of winning prizes.[60]

Let t_O index the month in which an outcome is observed, and t_E index the month in which the consumer wins the lottery (the "event-month"). Define $k \equiv t_O - t_E$ as the number of "periods" or months after/before the lottery win. I performed this re-weighting exercise separately for each of the 12 lotteries, and each prize level between U.S. $10 and U.S. $35, and also for U.S. $125 and U.S. $500 prizes. I then collapsed the data for each lottery by group g and period $k, k \in [-6, 6]$, using the DFL weights, and I took the average number of SSN receipts across the 12 lotteries.

Figure 8 displays the average number of receipts for which lottery winners and non-winners ask by six different prizes levels and $k \in [-3, 3]$. The x-axis shows the distance in months to the lottery or "event-month." Each graph displays the estimated DD coefficient

reinforcement learning in investors' behavior: personally experienced outcomes are overweighted in future choices.

[59] Figure C.2.a in the Online Appendix C shows an example of the distribution of lottery ticket holdings among winners and non-winners. It is clear that the winner group typically holds more lottery tickets. Since the number of lottery tickets is determined by consumers' participation, it is important to carefully control for the odds of winning.

[60] For a detailed description of DFL-reweighting, see Appendix B of Yagan (2015). For details of this specific application, see Online Appendix B.2

from estimating the following equation on the collapsed data for $k \in [-6, 6]$:

$$y_{gj} = \gamma_j + \pi_g + \beta \cdot I\{j \geq 0, g = T\} + u_{gj}, \tag{9}$$

where y_{gj} is the average number of SSN receipts group g asks in "event-month" j. Figure 8 shows that there is a significant difference in behavior between lottery winners and non-winners for all prize levels displayed. As the size of the lottery win grows, the estimated effect is larger. This pattern indicates that the change in behavior is indeed due to the lottery win, and that consumers are attuned to the lottery results. Figure 8.c shows that the 5-dollar win affects not only the number of receipts a consumer asks for, but also the number of different businesses in which a consumer asks for receipts. In order to further investigate the effect of winning a lottery, Figure C.2.b in the Online Appendix C plots the effect of 5 dollar prize differences for different levels of prizes. The effect of winning a lottery prize at all is relatively larger than the effect of incremental prizes of similar size on consumer participation.

The evidence is consistent with a behavioral explanation, given that there is a significant 0.6% difference between the number of receipts lottery winners and non-winners ask for even for a U.S. $5 prize, and effect persists across months. Since the odds of winning are independent of past wins, the change in behavior observed in Figure 8 suggests that lottery wins could be working as a nudge by making the odds of winning more salient and reinforcing the propensity to ask for receipts. Alternatively, consumers could be using the past lottery win as a signal of luck, and therefore perceive a higher expected return from participating in the program. Since the effect is increasing in the lottery size, it is possible that the size of the prize matters for strength of the signal. The effect, however, is confounded with the fact that larger prizes are more relevant cash shocks that can increase the level of overall consumption.

An alternative explanation is that consumers use lottery wins as evidence that the program works as advertised. Figure 8.b shows the effect of a U.S. $5 win for a sample of individuals that won the lottery once before, in which the effect of confirming that the program works should not be as relevant. I find a 0.7% statistically significant difference in the number of receipts consumers ask for this subsample.

The data does not allow to tease out the exact behavioral mechanism that the government is exploiting, but the evidence suggests that the lottery component can be a relevant mechanism to explain how the NFP can generate enough consumer participation to improve enforcement. Lotteries are used in other contexts such as lottery-linked savings accounts offered by commercial banks, possibility exploiting similar biases. Also, if people misperceive probabilities or simply have a taste for playing lotteries, it would be more costly for firms to match government's incentives. Not only it could increase the necessary discount to make consumers let go of the receipts, it could also create a friction in pinning down the right discount level.

The relative effectiveness of lotteries compared to tax rebates would be a relevant comparison for a cost-benefit analysis, but the variation in the data does not allow to distinguish the two in a compelling manner. The Online Appendix D.2 provides some suggestive evidence that lotteries might be relatively more effective. Consumers sharply increase their overall participation in the program around the time that they become eligible for lotteries, even though the expected value of lottery rewards is substantially lower than the tax rebates.

5 Implications for tax policy

The empirical analysis performed in section 3 shows that incentives for consumers to ensure that firms accurately report transactions can be an effective way to improve firm compliance in final sales transactions. The policy implications, however, depend on the costs and benefits associated to this policy, and the potential alternative investments in enforcement technology.

The government of Sao Paulo is forgoing part of the tax revenue collected at at the final consumer stage: both incremental revenue from the program, and infra-marginal revenue. Therefore, it is not clear that the program is able to increase revenue net of transfers. The government is rewarding consumers with 33% of the tax collected in final sales transactions: 30% in tax rebate and 3% in lottery prizes. Thus the 22% increase in compliance reported in section 3 would imply that the potential increase in tax collection would not be enough for the government to break even. However, the NFP is arguably relying on the fact that some consumers may never collect rewards. As of 2011, 50% of the rewards were not collected. In particular, there are 27 million consumers that asked for SSN receipts but did not enroll online in the first four years of the program, which is the only way one can claim rewards. If one only takes into account rewards claimed by consumers, the program would be breaking even. It is important to consider, in addition, that the 22% increase is a lower bound for the effect of the program, so the total potential increase in tax collection could be larger and the program could be generating additional revenue net of rewards.

The rewards, however, can arguably be considered as transfers and not costs. There may also be redistributive benefits if lower-income individuals value lotteries relatively more and consume a larger share of their income; or if the government puts a higher weight on consumers than on tax evaders.[61] The program also allows consumers to donate their rewards to charities, which may increase utility from altruistic motives. In addition, consumer-reward programs are often framed as a way to encourage a culture that values tax compliance (or "tax morale"). If this channel is relevant, the program could potentially generate a shift in consumer's propensity to ask for receipts even if the government eventually discontinues or reduces the rewards. Costa and Gerard (2015) argue that neglecting hysteresis in household behavior could overestimate the social cost of corrective policies.

Additionally, improving enforcement can also help tilt the playing field in retail away from firms that evade taxes toward the most-efficient firms. In fact, if there is heterogeneity in compliance and this new monitoring strategy affects tax payers that usually get away with evasion, the policy could improve horizontal equity. There could also be fiscal externalities to the federal tax authority that levies other taxes on firms that could benefit from the increase in compliance and information generated by the state-level program. Nonetheless, it is possible that there are other margins of evasion that increased as a result of this policy.[62]

The data does not allow for comparisons with alternative enforcement strategies such as the usual direct audits. Arguably consumer monitoring augments the deterrence effect of usual audits, which could even allow a decrease in audit rates. Developed countries typically have high levels of compliance despite low audit rates, which can be in part attributed to information availability (Kleven, 2014). In the NFP case, new information elicited from consumers participation in the program could potentially increase the ability

[61] According to Andreoni et al (1998) it is an unresolved issue whether governments put different weights on cheaters vs. honest tax payers.

[62] For instance, firms could be switching to informal labor or they could be evading other taxes that are not affected by this new monitoring policy. Carrillo, Pomeranz and Singhal (2015) find that an increase in enforcement was followed by taxpayers making offsetting adjustments on less verifiable margins in Ecuador. Although expenses claimed could have increased in Sao Paulo, the offsetting effect does not seem large enough, as the effect of the program on taxes paid is similar to the effect of the program on reported revenue as reported in the Online Appendix C.

of tax authority to detect evasion in audits or optimize audits.[63]

Nonetheless, there could be non-trivial costs borne by the consumers that participate in such reward programs. Berhan and Jenkins (2005) argue that policies that introduce incentives for consumers to ask for receipts usually have high participation costs. The administrative burden is normally borne by consumers that often need to submit physical copies of receipts to the government to get rewards. NFP's implementation is innovative in reducing participation costs to consumers. It leverages the fact that establishments must report receipts electronically to the tax authority regardless of whether the receipts have a consumers SSN attached to it. However, consumers need to pay a time cost to spell out their SSN and to enroll online, and it could impose additional waiting time for other customers.

Participation costs matter not only to compute the cost imposed on consumers, but also to determine the take up in such programs. A large enough take up could be crucial to increase firm compliance, and generate infra-marginal receipts. In the case of NFP, 1% of consumers filed complaints about 20% of firms. This is not necessarily surprising as the number of consumers is much larger than the number of firms, but it highlights how this diffuse monitoring mechanism can improve enforcement even when most consumers are not willing to actively participate in complaints. Arguably firms do not know which consumers among many that are asking for receipts are willing to be whistle-blowers, so the government could exploit this information asymmetry to generate a deterrence effect from this diffuse monitoring.

There are arguably ways to make the policy more cost-effective. For instance, Sao Paulo has created a SSN barcode card to mitigate participation costs: consumers may scan the card at the moment of the purchase instead of verbally reporting the SSN for every transaction. Importantly, millions of people are already participating and have paid the fixed cost of setting up online accounts. Given the take-up NFP has already achieved, the program could potentially change some of the incentives to become more cost-effective in the future. Perhaps the rewards could rely more on lotteries, relative to tax rebates. It would be important to build more evidence on the relative cost-effectiveness of different reward options – tax rebates, lottery in-kind prizes or cash lottery prizes – that are

[63]For instance, the patterns of receipt reporting by establishments can be used to trace evasion. Consumers often forget or decide not to ask for receipts, so establishments are not expected to report 100% of receipts with SSN. From 2009 to 2011, 18% of establishments reported 100% of receipts with SSN across all months, which suggests that establishments might be selectively reporting transactions to the tax authority only when consumers ask for receipts.

common in policies that incentivize consumers against tax evasion.

6 Conclusion

Access to substantial third-party information trails is widely believed to be critical for modern tax enforcement. This paper has investigated how the availability of third-party information can improve firms' compliance. I exploit administrative data and quasi-experimental variation from a policy that rewards consumers for ensuring that firms accurately report final sales transactions to the government in Sao Paulo, Brazil.

I find that the program increased revenue reported in retail sectors by at least 22% over four years. I examine heterogeneity across establishments and consumer responses to rewards to shed light on the mechanism through which third party reporting can improve compliance despite collusion opportunities. I find that the estimated effect is stronger for sectors with a high volume of transactions, consistent with shifts in detection probability due to whistle-blower threats. I also provide direct evidence on the enforcement effect triggered by consumers blowing the whistle: firms report 14% more receipts and 6% more revenue after receiving their first complaint.

Furthermore, I show that consumers are finely tuned to the incentives of the program, and I exploit the random component of lottery rewards to investigate the effect of lotteries on consumer engagement with the policy. I find that that consumers condition their participation on past lottery wins. Even small prizes generate a significant and steady increase in the number of receipts consumers request, and in the number of different businesses in which they ask for receipts. The results are consistent with the possibility that lotteries amplify consumer responses due to behavioral biases, which would make it more costly for firms to try to match government incentives in order to collude with consumers.

The findings of the paper are consistent with the argument that whistle-blower threats and collusion costs could help to explain how self-enforcing incentives can be effective to harness third-party information in a context of extensive opportunities for tax evasion. From a policy perspective, this study sheds light on how citizen engagement can be used as a monitoring tool in hard-to-tax sectors with numerous small taxpayers in a participatory program. In the context of VAT systems, the results indicate that incentives to consumers can potentially help address the last-mile problem of the VAT, which is a well-known shortcoming of one of the most important and prevalent tax instruments in the world. In particular, the paper provides supporting evidence that consumers respond to lottery incentives to ask for receipts, which is the most common policy reward used by governments to mobilize consumers against tax evasion.

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TABLE 1: DESCRIPTIVE STATISTICS

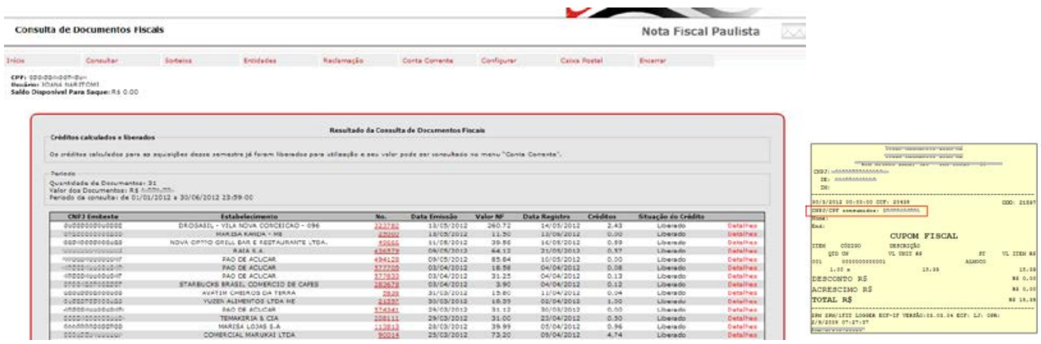
	Number of Obs.	Mean	Std. Dev.	Time Period
Establishment sample				
Retail establishments				
Reported revenue	66,382,628	13,917	83,549	Jan.2004-Dec.2011
Number of receipts	8,083,008	648	5,261	Jan.2009-Dec.2011
Number of consumers - SSN receipts	8,083,008	85	1,737	Jan.2009-Dec.2011
Revenue from SSN receipts	8,083,008	16,308	2,042,087	Jan.2009-Dec.2011
Share of receipts with SSN	8,083,008	0.44	0.41	Jan.2009-Dec.2011
Wholesale establishments				
Reported revenue	6,888,041	67,169.69	196,069	Jan.2004-Dec.2011
Consumers sample				
Number of receipts	46,505,268	4.5	7.6	Jan.2009 - Dec.2011
Number of businesses	46,505,268	3.0	4.2	Jan.2009 - Dec.2011
Tax Rebate	46,505,268	2.9	7.7	Jan.2009 - Dec.2011
Total expenditure in SSN receipts	46,505,268	356.4	1,346.4	Jan.2009 - Dec.2011
Lottery sample				
Number of receipts	37,237,148	10.4	9.4	Jun. 2010 - May.2011
Number of businesses	37,237,148	6.1	5.0	Jun. 2010 - May.2011
Tax Rebate	37,237,148	5.6	10.1	Jun. 2010 - May.2011
Total expenditure in SSN receipts	37,237,148	653.6	1,688.1	Jun. 2010 - May.2011
Number of lottery tickets	37,237,148	4.0	26.3	Jun. 2010 - May.2011
Lottery prize value	37,237,148	2.2	10.9	Jun. 2010 - May.2011

Note: Tables present the number of observations, means, standard deviations, and time periods of the key variables for each sample. All values are in US dollars (US$1=R$2). Reported revenue is the gross reported revenue by establishment. *Number of receipts* is the total number of receipts an establishment reports to the tax authority. *Number of consumers - SSN receipts* is the total number of different Social Security Numbers (SSNs) to which an establishment issues a receipt. *Revenue from SSN receipts* is a sum of the total value of SSN receipts an establishment issues. *Share of receipts with SSN* is the total count of reported receipts with SSN over the total number of reported receipts by establishment. The sector sample aggregates revenue reported by all establishments by 7-digit sectors as described in the text. *Number of receipts* is the total number of SSN receipts for which a consumer asks per month; *number of establishments* is the number of different establishments for which a consumer asks for SSN receipts per month; *total expenditures with a SSN* is the total amount of money spent associated with the SSN receipts; *average receipt value* is the average value among all purchases represented by consumer's SSN receipts in a given month; *number of lottery tickets* is the total number of lottery tickets a consumer holds per month; *lottery prizes* is the number of lottery prizes and the value of lottery prizes per month.

TABLE 2: COMPLIANCE EFFECT – RETAIL VS. WHOLESALE

	log Reported revenue			
	(1)	(2)	(3)	(4)
DD (Post Oct 07 * retail)	0.253***	0.244***		
	[0.0629]	[0.0664]		
DD * High volume of consumers			0.484***	
			[0.0614]	
DD * Low volume of consumers			0.182**	
			[0.0701]	
DD * Small establishments				0.526***
				[0.0909]
DD * Large establishments				0.0722
				[0.0700]
3rd-order polynomial of establishment size * DD			X	
Dummy for high volume of transactions*DD				X
Time FE	X		X	X
Establishment FE	X		X	X
R-squared	0.78	0.79	0.78	0.78
Number of observations	1,080,676	681,151	1,080,674	1,080,676

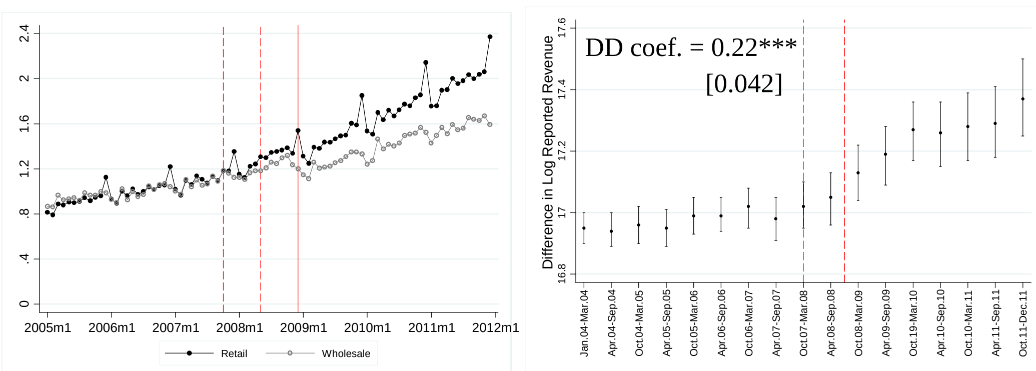
Note: Table 2 displays the main coefficients form regressions described in section IV. Standard errors are clustered at the 7-digit sector classification level (210 clusters). Significance levels *** 1%, ** 5%. The variable DD is defined as the interaction between a dummy for retail sectors and a dummy that equals 1 for time periods after Oct 2007. This table displays the regression coefficient of a DD regression using the establishment-level data. The dependent variable is log of reported revenue by establishment, and the data is collapsed into two periods: before and after Oct. 2007. The regressions are dollar- weighted (each observation is weighted by its pre-NFP value) such that each observation contributes to all regression estimates according to its economic scale to best approximate the aggregate effect. Column (1) shows the average DD estimate controlling for time and establishment fixed effects. Column (2) runs the same regression in a sample that restricts attention to firms that have been active since Jan. 2004. Column (3) splits retail sectors into two groups: sectors below the median volume of transactions distribution across sectors (Low volume of receipts) and sectors above the median of volume of transactions (High volume of receipts). Volume of receipts is defined by ranking 7-digit retail sectors by the average number of transaction by establishment between 2009 and 2011. In order to control for establishment size effects the regressions in columns (2) and (3) include a 3rd order polynomial interacted with the DD variable. Column (4) splits the retail establishments in two groups: establishments below the median establishment size distribution (Small establishments) and establishments above the median (Large establishments), and flexibly control for differential effects from volume of consumers by interacting the DD variable with five dummies for quintiles of volume of consumers. Size is defined by the total reported revenue by establishments during a four-year period before program implementation.



a. Online Account **b. Receipt**

FIGURE 1: ONLINE ACCOUNT AND *NOTA FISCAL PAULISTA* RECEIPT

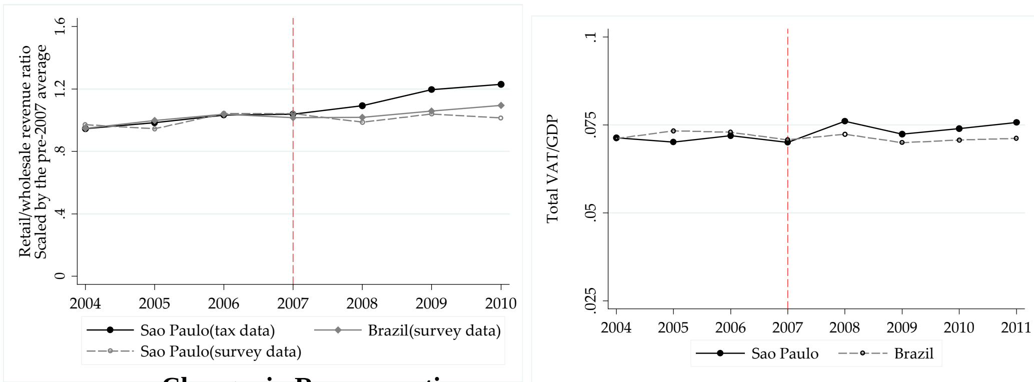
Note: Figures a and b are snapshots of an online account example at https://www.nfp.fazenda.sp.gov.br. The snapshot is from the author's online account. Tabs on the top of both figures can be translated (from left to right) as: *Home*, *Queries*, *Lotteries*, *Charities*, *Complaints*, *Current Account*, *Settings*, *Inbox*, *Sign out*. Figure a shows an example of an online account at the tax authority website under the tab "Check receipts": a list of all receipts, the issuing date, total value of each receipt, tax rebate, and a link to the details of each receipt. The tabs allow consumers to file complaints, verify whether they got a prize in a lottery, request deposits in a bank account, transfers to other enrolled consumers or transfers to charity. Figure b shows the receipt if one clicks on the last column in Figure a for details of one of the purchases listed. The receipt has a field to fill in the consumers' SSN – as highlighted in Figure b.



a. Raw data: reported revenue changes **b. Difference coefficients for 6-month time bins**

FIGURE 2: COMPLIANCE EFFECT – RETAIL VS. WHOLESALE

Note: Figure a shows reported revenue changes for retail and wholesale sectors. It plots the reported revenue by all establishments aggregated by retail or wholesale scaled by the average monthly reported revenue before Oct. 07 for each sector group. The figure plots the raw data, so there are spikes around December of each year due to seasonal variation in consumption. The vertical lines highlight the key dates for the implementation of the NFP program: phase-in of sectors begins in Oct.07 and ends in May.08, and the first lottery based on the purchases with SSN receipts was introduced in Dec.2008. Figure b plots regression coefficients from estimating specification (1) using a sample of 210 sectors between Jan 2004 and Dec 2011. The sector sample has 24,990 observations. The difference in differences (DD) coefficient displayed in the figure is estimated using the specification (2) where the DD variable is defined by the interaction between a dummy for retail sectors and a dummy that equals 1 for time periods after Oct 2007. Standard errors are clustered by sector. Significance levels *** 1%, ** 5%.



a. Changes in Revenue ratio - Retail v. Wholesale

b. VAT as a share of GDP

FIGURE 3: COMPARING SAO PAULO WITH BRAZIL

Note: The figure a shows changes in the retail-wholesale reported revenue ratio from the Sao Paulo tax data (black line), and changes in the retail-wholesale actual revenue ratio from a national-wide survey on the trade sector (gray lines). The dashed vertical line marks the beginning of the NFP program in 2007. The solid gray line displays the national-wide ratio (excluding Sao Paulo), and the dashed gray line shows the retail-wholesale actual revenue ratio for the state of Sao Paulo from the survey data. Each line is scaled by the pre-2007 retail-wholesale revenue ratio. The national ratio is based on the total gross revenue from sales, and retail revenue considers retail and motor-vehicles trade. The figure b shows total VAT revenue in Sao Paulo as a share of GDP comparing with total VAT collected in Brazil as a share of the total GDP in Brazil using data from the Brazilian Central Bank. The figures for Brazil include all Brazilian states leaving Sao Paulo out.

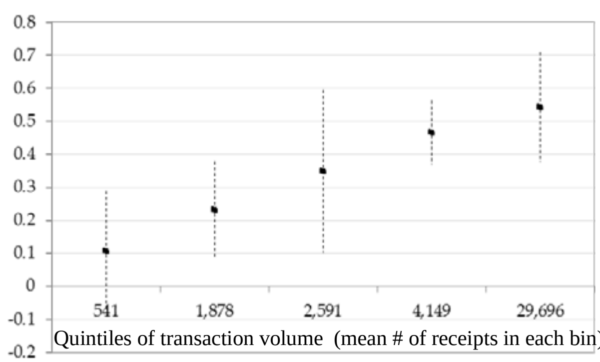
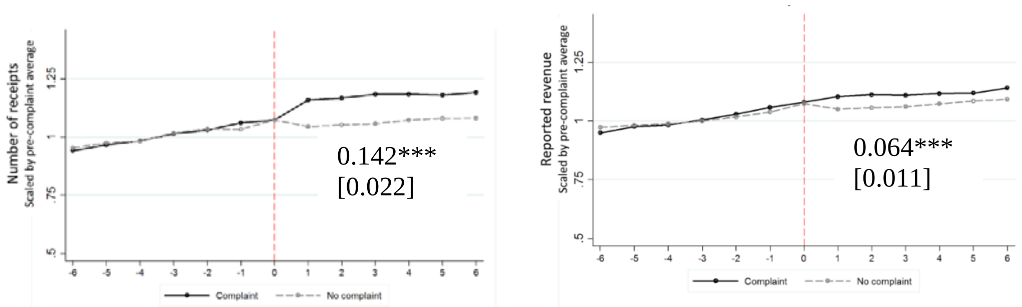


FIGURE 4: HETEROGENEOUS COMPLIANCE EFFECTS – WHISTLE-BLOWER THREATS

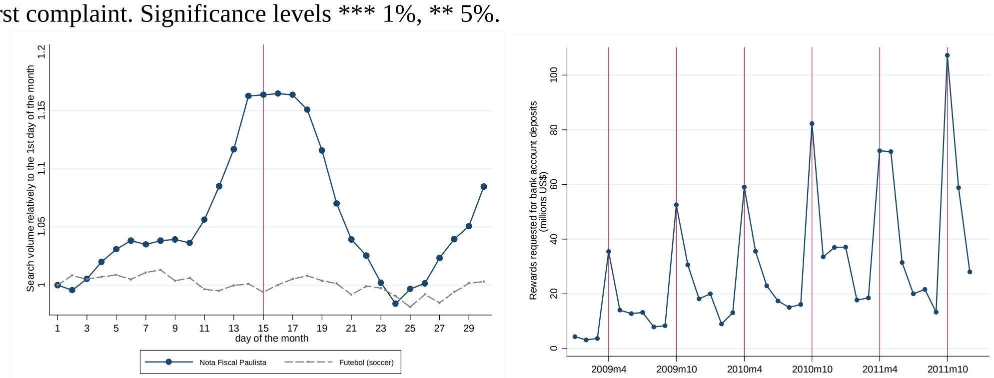
Note: The figure plots the coefficients and a 95% confidence interval from estimating equation (7) in section IV.A The figure plots the effects of the program by quintiles of the volume of receipts distribution. Volume of receipts is defined by ranking retail sectors by the volume of transaction as described in Section IV.A. The x-axis displays the average number of receipts across sectors in each bin. In both graphs standard errors are clustered by 7-digit sector classification (210 clusters). The sample is the same as in Figure 2. The dependent variable is log reported. In order to control for establishment size effects the regression includes a 3rd order polynomial interacted with the DD variable.



a. Changes in the number of receipts issued **b. Changes in reported revenue**

FIGURE 5: WHISTLE-BLOWER EFFECT ON FIRM COMPLIANCE

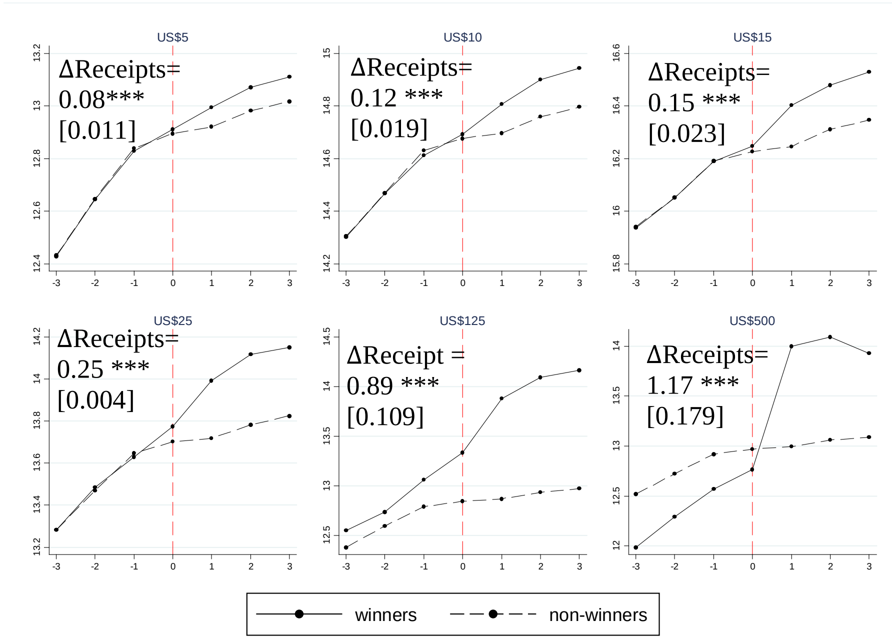
Note: Figures a and b plot the changes in the total number of receipts a firm reports and the changes in revenue reported to the government after the firm receives the first complaint. Both graphs display changes across event-time where each data point is scaled by the outcome's average before the first complaint (event-time zero). The 'Complaints' group is composed by firms that received their first complaint at event-time zero. The 'No complaint' group is composed by firms that did not receive their first complaint at time zero, and firms that did not receive a complaint until Dec. 2011. The outcome is averaged across groups and event times using weights based on quartiles of the propensity score to get the first complaint in a given time period. The propensity score is estimated using time specific trends for each sector, age of the firm, number of establishments by firm, dummy for establishment-headquarter, dummies for legal nature of the firm, sector and time fixed effects, dummy for location in the metropolitan region of Sao Paulo, and the three lags of third-order polynomials of reported revenue, reported receipts, SSN receipts and number of consumers. The estimated DD coefficient displayed in each graph is based on estimating specification (8) using the weighted averaged data by group 6 months before and after the first complaint. Significance levels *** 1%, ** 5%.



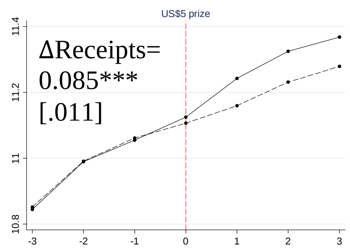
a: Timing of lottery results - Google searches for *Nota Fiscal Paulista*. **b: Timing of tax rebate disbursements - Rewards claimed by consumers**

FIGURE 6: ARE CONSUMERS PAYING ATTENTION TO THE REWARDS SCHEDULE?

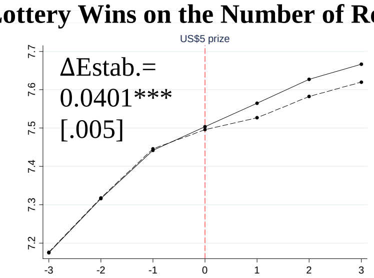
Note: Figure a displays the search volume from Google Trends website for Google searches with terms related to "nfp" or "nota fiscal paulista" or "nota paulista" pooled by day of the month from IPs addresses in the state of Sao Paulo between 2008 and 2011. It also displays searches for "futebol" (soccer in Portuguese) pooled by day of the month from IPs addresses in the state of Sao Paulo for the same time period. The lottery results are released around the 15th of each month marked by the solid vertical line. In Figure b each data point is the total amount in millions of US$ requested for direct deposit in consumer's bank accounts. As described in section II.B, the tax authority does a biannual disbursement of the tax rebates: every April and October.



a. The Effect of Different Sizes of Lottery Wins on the Number of Receipts



b. Impact of winning US$5 on the number of receipts among consumers that won a prize before



c. Impact of winning US$5 on the number of different establishments in which consumers ask for receipts

FIGURE 7: THE EFFECT OF LOTTERY WINS ON THE NUMBER OF RECEIPTS

Note: The x-axis is the number of months since the individual participated in a lottery. The graphs were constructed from the lottery sample described in section III and Online Appendix B. Figure a plots the results for different prizes. In each of the lotteries there are 1,407,394 prizes of U.S. $5, 76,303 prizes of U.S. $10, 15,000 prizes of U.S. $25, 1,000 prizes of U.S. $125, and 300 prizes of U.S. $500. Because it is common for individuals to hold more than one lottery ticket in a month, there are many cases of consumers that get a total of US$15 by winning a combination of a U.S. $5 and a U.S. $10 prizes. Figure b shows the effect of a U.S. $5 lottery win for consumers that have won a lottery once before. Figure c plots the number of different establishments in which consumers ask for receipts. Before taking the averages in each case, I create bins for each possible number of lottery ticket holdings from 1-40 tickets in each monthly lottery for 12 lotteries between June 2010 and May 2011. Then I re-weight the non-winners group such that each bin carries the same relative weight as the winner group distribution across lottery ticket holdings. The estimated DD coefficient displayed in each graph is based on estimating specification (9) using the weighted averaged data by group 6 months before and after the lottery. Significance levels *** 1%, ** 5%.

Online Appendix A: Data on Establishments and Consumers

Section II.C describes establishment-level and consumer-level variables and samples used in this paper. This appendix provides additional information on the datasets and variables, as well as further details on the re-weighting exercise from Sections IV.A and IV.B.

A.1. Establishments

Establishment data. In order to construct the establishment sample I combine two different sources of data. Due to confidentiality reasons, each dataset used to construct the *establishment data* was de-identified, and a "fake" identifier was created for each establishment. The first data source are tax forms from establishments in the tax regime RPA ("Regime Periódico de Apuração") that requires establishments to report their gross revenue, tax credits and tax debits monthly through a form called GIA/ICMS ("Guia de Informação e Apuração do ICMS") to assess the total VAT due by the establishment in a given month. The second source of data is composed by tax forms from establishments in a simplified tax regime called SIMPLES. As is common in the implementation of the VAT across the world (Keen and Mintz, 2004), there is a threshold below which firms do not pay taxes over the value added. In the case of Brazil, firms that have yearly gross revenue of less than U.S. $1.2 million can choose to be in a simplified tax regime called SIMPLES in which firms pay taxes over gross revenue.

For the SIMPLES establishments I combined monthly data for establishments in Sao Paulo from three different sources: (i) tax returns from the state's *SIMPLES Paulista* in all months between 2004 and until June 2007; (ii) tax returns for the DASN-SP ("Declaração do Simples Nacional-SP") from July 2007 until the end of 2008; (iii) tax returns from DASN ("Declaração anual do Simples Nacional") between 2009 and 2011. The changes in data sources are due to the fact that there was a separate SIMPLES regime for federal and state taxes before June 2007. After that, states and federal government centralized in a single system all SIMPLES tax information, and there was a transition period in which states and the federal government kept separate records.[64]

A.2. Consumers

Receipt data. The receipt data is constructed from a dataset that has transactions with SSN-identified receipts between January 2009 and December 2011. The transaction level data is a linked establishment-consumer data and has over 2.7 billion observations. The data was de-identified, and a "fake" identifier was created for each establishment and consumer. The datasets between October

[64]The datasets listed in (i) - (iii) have some months of overlap, which allowed me to cross-check the information available in each of them, and verify that these changes did not generate mechanical changes in revenue reporting.

2007 and December 2008 were not available to this study. The available data restricts attention to final consumers SSN ("CPF" holders), i.e., I do not have information on receipts issued with the SSN of other establishments or charities. Also, the data on approximately 90 consumers who won one of the top 3 lottery prizes of over U.S. $500 dollars in each monthly lottery between January 2009 and December 2011 were excluded from the dataset for confidentiality reasons.

Consumer sample. I take a 10% random sample of consumers who enrolled online by the end of 2011 – around 1.3 million people – and I construct a balanced monthly panel of consumer's participation in the program from the *receipts data* containing 46,505,268 observations between January 2009 and December 2011. In the case of three variables I describe in Section II.C – *number of receipts*, *number of establishments, total expenditures with a SSN* – for each individual I replace with zero the missing data in time periods in which no receipt with her SSN is reported by an establishment. The variable *average receipt value* is conditional on at least one receipt being issued with the consumer's SSN.

Online Appendix B: Complaints and Lotteries re-weighting Consumers

B.1. Complaints and re-weighting

Complaints data. For each firm I identify the time of the first complaint they ever received. In order to perform the empirical exercises on the effects of complaints on firms reported revenue in Section IV.A I merge the *Establishment sample* data with the *receipts data* described in section II.C. The combined dataset of reported revenue and reported receipts covers the time period between Jan. 2009 and Dec. 2011. For the event-studies, I consider all first complaints between June 2009 and May 2011, i.e., at least 6 months before and after the earliest and latest first complaint respectively. The complaints sample covers firms in the retail sector that issued at least one receipt before June 2009. 25% of firms received at least one complaint in the period of analysis.

Re-weighting.I use a propensity re-weighting method to flexibly control for the probability of getting a complaint such that I use a quasi-random component of the timing of the first complaint by matching groups that have similar odds of getting a complaint. I estimate a propensity-score of a firm receiving the first complaint for every month-year between June 2009 and May 2011 based on pre-event characteristics.[65]. Then I use quartiles of the propensity score to re-weight establishments that did not received their first complaint in the given month-year to compare with establishments that received their first complaint in that month-year.

I perform this re-weighting exercise separately for each period between June 2010 and May 2011. For each case, I restrict attention to the sectors that had at least one firm that received a complaint in a given date and I draw a 10 percent random sample of firms that did not receive the first complaint on that date to build the no-complaint sample. This sample includes both establishments that did not receive their first complaint in a given date and establishments that did not receive any complaint by Dec. 2011. The propensity score is estimated using a logit model on time specific trends for each sector, age of the firm, number of establishments by firm, dummy for establishment-headquarter, dummies for legal nature of the firm, sector and time fixed effects, dummy for location in the metropolitan region of Sao Paulo, and the three lags of third-order polynomials of reported revenue, total number of receipts issued, total number of SSN receipts issued and total number of consumers.

Once I create the propensity score, I construct a dataset for each month within this period, where I keep all firm that received their first complaint that month and all firms that did not receive their first complaint that month and I re-weight the no-complaints group to match the complaints group within each quartile of the propensity score distribution. I collapse each cohort of complaints by each group and "event-month" using the weights.

[65]I follow a similar method to Hilger (2014) that uses propensity-score re-weighting in the context of parental job loss effects on children's long-term outcomes.

B.2. Lottery wins and re-weighting

Lottery data. The lottery sample covers consumers that hold fewer than 40 lottery tickets in a given month for 12 lotteries between June 2010 and May 2011. In order to perform the empirical exercises on the effects of lottery wins on consumer participation in Section IV.B I merge this data with the *receipts data* described in section II.C. The combined dataset of lotteries and receipts covers the time period between January 2010 and November 2011, i.e., 6 months before and after the first and last lottery. As in the *consumer sample*, I balance the panel of consumer participation and replace missing values by zero for the two key variables I use *number of receipts* and *number of establishments.*

Re-weighting. Since the number of lottery tickets is determined by the total value of a consumer' purchase 4 months before the lottery draw, the more a consumer participates in the program by asking for receipts, the higher are the odds she will get a prize in a given lottery. Therefore, it is important to carefully control for the odds of winning a prize in order to study the effect of lottery wins on consumer participation. As I describe in Section IV.B, I use a re-weighting method based on DiNardo, Fortin, and Lemieux (1996) to flexibly control for the number of lottery tickets individuals hold to ensure I use the random component of the lottery by matching the two groups based on the odds of winning prize.

Figure A shows two examples of the distribution of lottery ticket holdings among winners and non-winners in monthly lotteries. The two examples look very similar, and it is clear that the winner group typically holds more lottery tickets. I create bins for each possible number of lottery ticket holdings up to 40 tickets, which is the set of lottery tickets for which there is common support between the two groups. In the case of prizes that are only possible by winning a combination prizes – e.g., a U.S. $15 total prize is always a result of winning a US$5 prize and a US$10 prize -, I restrict attention to lottery ticket holdings between 2 and 40 tickets. I then re-weight the non-winners group such that each bin carries the same relative weight as the analogous bin in the winner group distribution across lottery ticket holdings.[66] Once I create the DFL weights I collapse the *lottery wins data* by each group and "event-month" using the weights for each prize level I display in Figure 7.

I perform this re-weighting exercise separately for each lottery win I study in Section IV.B. I construct a dataset for each prize level as described in *lottery wins data* above, where I keep all consumers that won a given prize (winners) and all consumers that do not win any prize (non-winners). When I compare the effect of different prize values, the pool of non-winners is the same in each lottery across the datasets I create for each prize level but they are re-weighted differently depending on the prize I am considering since the winners group of different prize levels may have slightly different distributions of lottery ticket holdings.

[66]See Appendix B of Yagan (2015) for a thorough description of DFL re-weighting.

Online Appendix C: Additional Figures and Tables

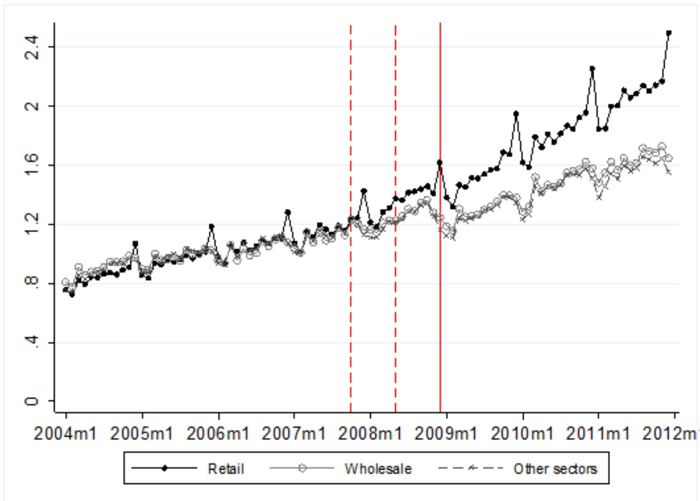


FIGURE C.1. COMPLIANCE EFFECT RETAIL VS. WHOLESALE VS. ALL OTHER SECTORS

Note: Notes: Similarly to Figure 3a, it shows reported revenue changes for retail and wholesale sectors, but it also adds all the remaining sectors as a third category. Each line is defined by the reported revenue by all establishments aggregated by retail or wholesale or other sectors scaled by the average monthly reported revenue before Oct. 07 for each sector group in constant prices. The figure plots the raw data, so there are spikes around December of each year follows the seasonal variation in consumption. The vertical lines highlight the key dates for the implementation of the NFP program: phase-in of sectors begins in Oct.07 and ends in May.08, and the first lottery based on the purchases with SSN receipts was introduced in Dec.2008.

TABLE C.1—COMPLIANCE EFFECT ROBUSTNESS TOP CODING AND STANDARD ERRORS

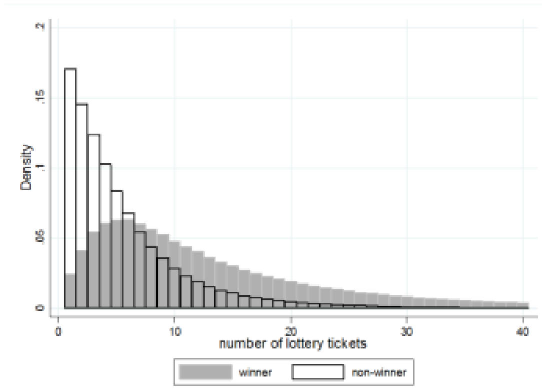
	winsorizing at 1%		winsorizing at 0.1%		winsorizing at 5%	
	across all month-years	within month-year ranks	across all month-years	within month-year ranks	across all month-years	within month-year ranks
Panel A: Establishment-level regression	[1]	[2]	[3]	[4]	[5]	[6]
DD (Post Oct. 2007* retail)	0.253***	0.208***	0.324***	0.302***	0.190***	0.200***
Std. Error clustered by sector	[0.0629]	[0.0654]	[0.108]	[0.110]	[0.0425]	[0.0456]
Std. Error clustered by establishment	[0.0228]	[0.0232]	[0.0542]	[0.0555]	[0.0134]	[0.0134]
Time FE	x	x	x	x	x	x
Establishment FE	x	x	x	x	x	x
Adjusted R-Squared	0.779	0.784	0.805	0.807	0.724	0.723
Number of Observations	1,080,676	1,080,676	1,080,676	1,080,676	1,080,676	1,080,676
Panel B: Sector-level regression						
DD (Post Oct. 2007* retail)	0.219***	0.181***	0.196***	0.186***	0.250***	0.262***
Std. Error clustered by sector	[0.0429]	[0.0429]	[0.0519]	[0.0518]	[0.0351]	[0.0347]
Time FE	x	x	x	x	x	x
Sector FE	x	x	x	x	x	x
Adjusted R-Squared	0.98	0.98	0.97	0.97	0.99	0.99
Number of Observations	20,160	20,160	20,160	20,160	20,160	20,160

Note: Panel A reports result for the preferred specification used in the paper is reported in [1] winsorizing gross revenue at 1% across all month-years, and includes only wholesale establishments in the control group. Column [2] reports the results when winsorizing at 1% within month-year ranks. Columns [3] to [4], and [5] to [6] winsorize gross revenue at 0.1% and 5% respectively across all month-years and within month-year ranks. The variable DD is defined as the interaction between a dummy for retail sectors and a dummy that equals 1 for time periods after Oct 2007. The dependent variable is log of reported revenue by establishment winsorized as indicated, and the data is collapsed into two periods: before and after Oct. 2007. The regressions are dollar- weighted (each observation is weighted by its pre-NFP value) such that each observation contributes to all regression estimates according to its economic scale. Standard errors are clustered at the 7-digit sector classification level (210 clusters). Standard errors clustered by establishments are reported in brackets. Panel B reports the results using data aggregated by sector for different choices of top coding. Column [1] shows the results reported in Figure 2b winsorizing gross revenue at 1% across all month-years, and the other columns follow the same logic as Panel A. Significance levels *** 1%, ** 5%.

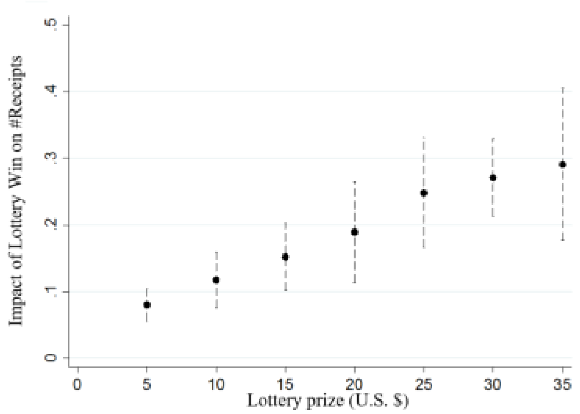
TABLE C.2—COMPLIANCE EFFECT ROBUSTNESS TAX REVENUE WITHOUT WITHHOLDING

	exclude sectors with > 1% withholding			
	Sector-level regression		*Establishment-level regression*	
	ln (Reported Revenue)	ln (Tax Revenue)	ln (Reported Revenue)	ln (Tax Revenue)
	[1]	[2]	[3]	[4]
DD (Post Oct 07* retail)	0.309***	0.414***	0.340***	0.330***
	[0.0633]	[0.137]	[0.0847]	[0.107]
Sector FE	x	x	x	x
Time FE	x	x	x	x
Adjusted R-Squared	0.98	0.94	0.807	0.841
Number of Observations	5,088	5,069	145,293	145,293

Note: Table C.2 displays the main coefficients for the same specification as Table C.1. The table restricts attention to a subsample of firms in sectors with less than 1% of VAT withholding. Withholding is defined by product, and the data does not indicate which products are sold by firms. But for a subset of firms it is possible to measure what percentage of VAT debits and credits is affected by withholding. Based on this subset of firms and their sector of activity, I flag all sectors where these firms have less than 1% of VAT withholding. Column [1] and [2] shows the DD effect using data aggregated by sector for reported revenue and tax revenue respectively. Columns [3] and [4] display the results using establishment level data. The variable DD is defined as the interaction between a dummy for retail sectors and a dummy that equals 1 for time periods after Oct 2007. The dependent variable is log of reported revenue or log of tax payments (winsorized at 1%), and the data is collapsed into two periods: before and after Oct. 2007. The regressions are dollar- weighted (each observation is weighted by its pre-NFP value) such that each observation contributes to all regression estimates according to its economic scale. Standard errors are clustered at the 7-digit sector classification level (210 clusters). Significance levels *** 1%, ** 5%.



a. December 2009 Lottery tickets



b. The estimated effect of winning different sizes of lotteries on the number of SSN receipts

FIGURE C.2. LOTTERY TICKET HOLDINGS AND THE EFFECT OF LOTTERY WINS

Note: Figure a shows examples of histogram for the number of lottery tickets winners and non-winners hold in December 2009. The figures only consider lottery ticket holdings under 40. A lottery ticket is generated for every 50 dollars a consumer spends in SSN receipts; so 50 receipts of 1 dollar or 1 receipt of 50 dollars are equivalent, and generate 1 lottery ticket. There is common support between the two groups for lottery ticket holdings below 40, and the winner group holds more lottery tickets than the non-winner group. The graphs were constructed from the lottery sample described in section II and Online Appendix B. Figure b shows the effect of winning additional U.S. $5 across different prize levels. In each of the lotteries there are 1,407,394 prizes of U.S. $5, 76,303 prizes of U.S. $10, 15,000 prizes of U.S. $25, 1,000 prizes of U.S. $125, and 300 prizes of U.S. $500. Because it is common for individuals to hold more than one lottery ticket in a month, there are many cases of consumers that get a total of US$15 by winning a combination of a U.S.$5 and a U.S.$10 prizes. The estimated DD coefficient displayed in each graph is based on estimating specification (9) using the weighted averaged data by group 6 months before and after the lottery.

Online Appendix D: Additional Empirical Analysis

D.1. Effects on Employment and Exit

The observed enforcement affect could increase firms' tax liability, i.e., it can imply an increase in the effective tax rate. This change may affect establishments that were on the margin of exiting the market or firing employees. I analyze each effect in turn.

Employer-employee data. From the Brazilian Department of Labor, I use annual reported employment for all formal establishments in Brazil (RAIS/CAGED). The data covers all formal establishments that have at least one employee. All formal firms must report to the Department of Labor their employment information in a yearly basis. It comprises individual information of employees such as wages, hours, years of education, date of hiring, date of firing, and type of contract. I use a version of this data that aggregates the total number of employees by 5-digits sector definition.[67]

Employment sample. Because the data from the Department of Finance of Sao Paulo is de-identified, it cannot be matched with the employer-employee dataset (RAIS/CAGED). In order to analyze the impact of the program on employment, I construct a sample of establishments that follows as closely as possible the *establishment sample* from Sao Paulo.[68] I aggregate the employment sample by 5-digit sector definition to analyze the effect of the program on employment.

Exit. I define an establishment's month of exit as the last month I observe that establishment in the data, and I consider all exits between 2005 and 2010. The data for the analysis of exits comprise all establishments in retail and wholesale, i.e., without the restrictions from *establishment sample*. Figure 12a shows yearly exit rates by retail and wholesale sectors, where the exit rate is defined as the total number of exits in year t and sector s, divided by the total number of establishments in year $t-1$ in sector s.[69] The figure also shows the DD coefficient from estimating a specification similar to equation (6) in a 7-digit sector yearly panel, where the exit rate is the dependent variable. The coefficient is not statistically distinguishable from zero, which indicates that on average the policy did not affect establishments' decisions to exit during the period of analysis.[70]

[67]The sector of activity listed in RAIS/CAGED has 5-digits until 2008 (CNAE 2.0), and it has 7-digits from 2009 onward (CNAE 2.1). In order to construct a time series from 2004 to 2011 by sector, I used the CNAE 2.0. definition of sector with 5-digits. The change from 7-digits to 5-digits do not affect the retail and wholesale classification for most of the sectors. Only in the case of motor vehicle trade it is not possible to distinguish retail and wholesale with a 5-digit definition. In the results reported here I include motor vehicles trade in retail. The results do not change if I exclude these sectors.

[68]I exclude observations from establishments active after October 2007, and I only include establishments that were already operating by January 2004.

[69]I exclude 2011 because my sample period ends at the end of 2011. Therefore, I allow at least consecutive 12 months without observing a firm in the data to be sure that the firm exited.

[70]This result is robust to an alternative exit measure, where I consider as exit the last date I observe a firm report non-zero revenue. Many firms that do exit may still submit forms with zero activity to avoid or postpone the paperwork required to close a firm in Brazil.

Employment. To investigate employment effects I use the *employment sample* described in section II.C. As opposed to the tax data from Sao Paulo, this sample covers the entire country. As a result, I can use retail sectors in other states as a counterfactual for retail sectors in Sao Paulo. Figure 12b displays log employment in retail in Sao Paulo and in other states. The figure also shows the DD coefficient from estimating a specification similar to equation (6) in a 5-digit sector yearly panel, using log employment as the dependent variable and adding state fixed effects along with time and sector fixed effects. The coefficient is very close to zero, suggesting that the policy, on average, had no effect on establishments' formal employment decisions.[71]

The evidence above indicates that the increase in tax enforcement did not affect employment or exit decision of firms. However, it is possible that changes in employment and exit may occur after the period of analysis. The fact that I find no effect on employment is consistent with the increase in reported revenue being a reporting effect, rather than an actual increase in sales, in which case I could potentially observe an increase in employment or a drop in exit. As this is a reporting effect, it could impact the effective tax rate firms face and negatively affect the ability of firms to keep employees or survive in the market. The null effect indicates that the implied increase in the effective tax rate may not be large enough to affect the firm along these margins, and may just reduce evasion rents. The average tax paid over reported revenue was 4% before NFP, so a 22% increase in the effective tax rate might not be a large change in the net of taxes revenue.[72] Another explanation is that firms can potentially adjust other margins that I do not observe in the data such as, for instance, firing informally-hired workers.

D.2. The effect of lottery eligibility

In order to shed light on the relative effectiveness of tax rebates and lottery prizes, I next exploit the timing in which consumers enroll online and become eligible for lotteries. Consumers do not need to enroll online to start accumulating tax rebates, so the rebate incentive does not vary around the time the consumer creates her online account. Even though the timing of enrollment is not random, the most relevant incentive change when a consumers enrolls online is that she can opt in for lottery prizes.

I follow Jacobson, LaLonde, and Sullivan (1993) in estimating the dynamic effects of online enrollment on consumer participation in the program using an event-study design. I use the *consumer sample* described in section II, and I focus on four outcomes defined in section II: *number of receipts*, *number of establishments, total expenditures with a SSN, and average receipt value*. Let t_O index the

[71] Since the *employment sample* only covers formal employment, this exercise does not rule out the possibility that informal employment changed as a result of NFP.

[72] Moreover, establishments may be able to pass-through this tax increase to consumers. Data on prices and quantities – which have not been available for this project – would be needed to understand the incidence of the policy.

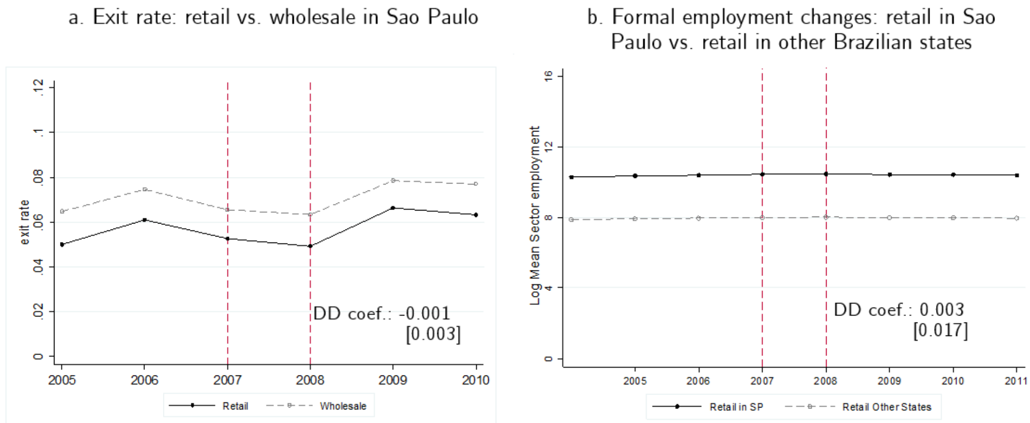


FIGURE D.1. THE IMPACT ON EXIT AND FORMAL EMPLOYMENT

Note: Figure 12a displays exit rates in retail and wholesale. Exit rate is defined as the total number of exits in year t and sector s, divided by the total number of establishments in year t -1 in sector s. Exit is the year I observe an establishment in the data, and I consider all exits between 2005 and 2010. The data for the exit analysis comprises all establishments in retail and wholesale. Figure 12a also displays the DD coefficient from estimating a specification similar to equation (2) in a 7-digit sector yearly panel with 1,260 obs., and using exit rates as the dependent variable. Standard errors are clustered at the 7-digit sector level. Figure 12b uses a different data source: a nationwide annual administrative formal employer-employee dataset that allows a within retail comparison. The employment sample aggregates the employer-employee data by 5-digit sectors. Figure 12b displays changes in the log employment in retail in Sao Paulo and retail in other states. The figure also shows the DD coefficient from estimating a specification similar to equation (2) in a 5-digit sector yearly panel and using log employment as the dependent variable, and adding state fixed effects. The data has 9,392 observations and covers all years between 2004 and 2011 in 27 states. Standard errors are clustered at the 5-digit sector level

month in which an outcome is observed, and t_E index the month in which the consumer enrolled or "event-month." Define $k \equiv t_O - t_E$ as "period" or months after/before event, then:

$$y_{i,t_O,t_E} = \sum_{j=-6}^{6} \beta_j \cdot I\{j = k\} + \gamma_i + \pi_{t_O} + u_{i,t_O,t_E} \tag{10}$$

where y_{i,t_O,t_E} is one of the four outcomes of interest, $I\{j = k\}$ is a dummy variable that is equal to 1 when $j = t_O - t_E$, γ_i refers to individual fixed effects, π_{t_O} models time fixed effects, and u_{i,t_O,t_E} is the error term that is clustered by municipality. This specification has individual and calendar time fixed effects, so I identify β_j by exploiting variation in the timing of enrollment. Figure D.2 displays the estimated $\hat{\beta}_j$ from Equation (10) and 95% confidence intervals, where $k = -1$ is the omitted category. In each graph, I add the sample mean before enrollment to facilitate interpretation.

Figure D.2 shows that consumers asked for four receipts on average with SSNs before they enrolled online, when they were only eligible for tax rebates. After enrolling at period zero, the average number of receipts that they asked for per month doubled, and the change seems to reflect a permanent level shift in participation. The number of different establishments in which a consumer asked for receipts also increases considerably in Figure D.2b. Figure D.2c shows that there is an upward trend in the total amount spent in SSN receipts before an individual enrolled online, but there is a sharp jump in the total SSN expenditure at the moment of registration. The average receipt value drops from U.S. $120 to U.S. $25 in Figure D.2d; so consumers were asking for receipts more often and more widely.

The effects described in Figure D2 cannot be exclusively attributed to the lottery eligibility since the decision to enroll online could be explained by a shock that affects both the decision to enroll and the change in behavior documented in the figures. Nonetheless, the sharp differences in participation between before and after online enrollment, and the fact that consumers conditioned their participation in the program on past lottery wins, are consistent with lotteries being an effective incentive device for consumers. Since lotteries are relatively less costly than tax rebates, a composition of rewards that puts more resources into lotteries relative to rebates may potentially be more cost-effective. More research is needed in order to pin down the relative effectiveness of $1 in tax rebate versus $1 in lottery prizes.

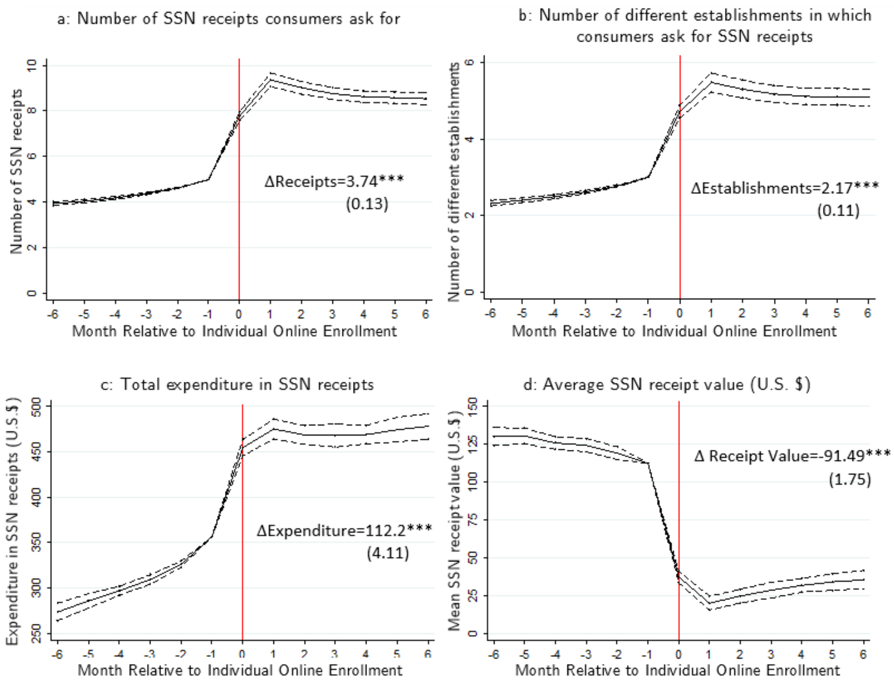


FIGURE D.2. THE EFFECT OF LOTTERY WINS ON CONSUMER PARTICIPATION

Note: The graphs plot coefficients and 95% confidence intervals from estimating equation (10) in a panel of a 10% random sample of consumers that were registered online by the end of 2011 – around 1.3 million people -, and 46,505,268 observations between Jan 2009 and Dec 2011. Number of receipts: the total number of SSN-identified receipts for which a consumer asks per month; number of establishments: the number of different establishments for which a consumer asks for SSN-identified receipts per month; total expenditures with a SSN: the total amount of money spent associated with the SSN-identified receipts, aggregated by consumer, per month; average receipt value: the average value among all purchases represented by consumer's SSN-identified receipts in a given month. In order to reduce the influence of outliers I winsorize the number of receipts and total expenditure with a SSN by their 99th percentile value. Significance levels *** 1%, ** 5%.