

# Learning Dynamics in Tax Bunching at the Kink: Evidence from Ecuador\*

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## Abstract

We explore the role of learning and experience in shaping behavioral responses to tax incentives and examine the mechanisms and margins of adjustments in taxable income. Particularly, we study the extent of bunching behavior in personal income taxes exploiting new administrative tax data from Ecuador. The unique setting of a rapidly formalizing economy with increasing numbers of taxpayers is the ideal environment to assess the effects of experience in tax paying on individual tax-filing behavior. Our results show that experience with the tax system strongly increases the chance of locating just below the first kink of the marginal tax schedule (“bunching”). This bunching is almost entirely driven by reporting behavior through generous deduction opportunities. By studying individuals who switch their jobs as well as firms that receive new employees, we disentangle adaption to general firm-level practices from learning through interaction with co-workers. We find very strong spillover effects at the firm level consistent with learning and memory but do not find effects of new employees on their co-workers’ tax-filing behavior. We conclude that firms seem to be the main driver of tax adjustment behavior.

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# 1 Introduction

Despite the predictions of labor supply models, empirical studies have only found limited evidence for bunching behavior at kink points in the marginal tax schedule. Information frictions are a commonly used explanation for the absence of pronounced spikes in the income distribution in the literature on behavioral responses to taxation. An important open question is how individuals that are new to the institutional setting of paying taxes react to incentives posed by the system. Moreover, there is no clear consensus on how information about tax adjustment opportunities is transmitted and what the driving factors of these adjustments are.

In this paper, we exploit new and very detailed administrative data on personal income tax (PIT) returns in a developing country, Ecuador. The environment of a rapidly formalizing economy with a steady inflow of new individuals to the tax system provides a unique setting to study the dynamics of tax responses. This is especially relevant since in the process of formalization, developing countries rely ever more on PIT (Besley and Persson, 2013). Particularly, we examine how workers' responses to jumps in the marginal tax rate (inducing kinks in their budget sets) change over time and with increasing experience and exposure to the tax system. Furthermore, we contribute to the literature by disentangling the effects that firm-level practices and co-worker behavior have on individual tax-filing.

Using new individual tax return data on the universe of formal-sector wage earners in Ecuador ranging from 2006 to 2015, we provide evidence for substantial sensitivity of reported taxable income to a discontinuous jump in the marginal tax rate. We observe a large and pronounced spike in the distribution of taxable income just before the income tax exemption threshold. We quantify the prevalence of this bunching behavior using an established bunching estimator which relates the excess mass in this area to an estimated counterfactual (Kleven, 2016). The effect is primarily driven by about 20% of the working population who take advantage of generous deduction possibilities in health, education, housing, clothing, and food. These deduction possibilities are the main part of the Ecuadorian government's policies to induce an increase in formalization. The tax

responses shown in the data represent reporting behavior rather than real labor supply responses as there is no indication of bunching in gross income. Most importantly, the mass of bunchers in taxable income increases with higher experience in filing taxes and stronger exposure to the tax incentives. This leads to the conclusion that workers in Ecuador learn about the incentives and measures to avoid paying taxes as they adjust to the system.

In our analysis, we shed light on how workers learn about these tax adjustment opportunities and what the predominant channels of information transmission are. Based on detailed employer-employee matched data and a research design that exploits job transitions, we can disentangle whether the observed learning patterns are mainly driven by individuals learning from firms (and firm-level institutions) or individuals learning from their co-workers.

In order to quantify how individuals learn about tax adjustment opportunities from their firm, we generate a sample of job switchers who change their main employer within our sample period and track the degree of bunching among their co-workers in the old and new firms. Our results show a strong and asymmetric adjustment to the prevailing bunching practices at the firm level. The probability to bunch for individuals who move to a firm in the top quintile of the distribution of bunching shares (from an origin firm in the middle quintile) increases by about 3-5 percentage points while it remains constant when moving to a firm in the bottom quintile, even when controlling for a range of individual and firm-level characteristics. We show that the effects are persistent and even increase their magnitude in the second year at the new firm. The asymmetry of the effects lends strong support to the hypothesis that knowledge spillovers and memory play an important role in determining individual tax-filing behavior. Particularly, our evidence is consistent with a model of learning and memory in which individuals learn about tax adjustment opportunities when moving into a high-knowledge environment. When moving to a low-knowledge environment, however, individuals retain their previous knowledge and maintain their behavior with respect to taxes.

To shed light on the second possible learning mechanism at work, namely individuals

learning from their co-workers, we generate a sample of firms that hire new employees. We compare bunching among incumbent employees in firms with incoming workers who were previously bunching to incumbent employees in firms with incoming workers who were not bunching before.<sup>1</sup> We find no evidence of workers learning about tax adjustment opportunities from new co-workers. Even among small firms and firms without any experience in bunching where we would expect larger effects, we cannot provide evidence for spillovers of new co-workers to incumbent workers. We conclude that in this setting, firms seem to be a much stronger driver of individual tax-filing behavior than a given employee’s co-workers.

The remainder of the paper is organized as follows. In section 2, we give an overview of the related literature and the contributions of this paper. Section 3 provides information on the institutional background in Ecuador and describes the PIT system in detail. Section 4 gives detailed information on the various data sources employed in our study. In section 5 we present the results from our analysis. Section 6 concludes.

## 2 Related Literature

Our paper contributes to the growing literature on bunching at kinks and notches in the tax schedule that was started by the seminal paper by Saez (2010). The method of estimating labor supply responses from the size of the excess mass at kinks and notches was further developed by Chetty, Friedman, Olsen, and Pistaferri (2011) and Kleven and Waseem (2013) and is thoroughly summarized in Kleven (2016). Evidence on behavioral responses to personal income taxation stems mainly from developed countries. Chetty et al. (2011) and Bastani and Selin (2014) analyze data from Scandinavia. They find bunching only at selected, particularly salient kinks (e.g., the top tax bracket) and for subgroups that can adjust their income relatively easily such as self-employed workers. In comparison, our results indicate relatively strong reactions to a very small kink.<sup>2</sup>

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<sup>1</sup>We only regard incoming workers with previous gross income in the range where bunching at the first kink would have been possible.

<sup>2</sup>The first kink in the Ecuadorian tax schedule is very salient. The change in marginal tax rates from zero to five percent, however, is very small in international comparison.

Moreover, we concentrate on bunching solely among wage earners. In line with large parts of the literature, we find bunching to be driven mainly through reporting behavior and not real labor supply responses. The generous deduction possibilities in Ecuador are an interesting environment to study in this regard since they lend workers considerable scope to adjust their reported income.

Evidence on knowledge diffusion and spillover effects in bunching is provided by Chetty and Saez (2013), Chetty, Friedman, and Saez (2013), and Paetzold and Winner (2014). These papers analyze the effect of moving to high- or low-bunching environments and find significant impacts of coworker/regional bunching shares on individual bunching. Moreover, their evidence is supportive of learning and memory as individuals increase bunching when exposed to high-bunching environments but keep bunching when moving into low-bunching environments.

Our contribution to this literature is threefold. First, we add the dimension of experience with the tax system and find important impacts of previous exposure to the system on the adjustment process. Second, we analyze bunching of job switchers on the firm level and find much stronger effects than the studies that examine aggregate effects on the regional level. Third, we disentangle learning effects at the firm-level from those occurring between co-workers.

Another related strand of the literature is concerned with behavioral responses to taxes in developing countries. Kleven and Waseem (2013) and Best, Brockmeyer, Kleven, Spinnewijn, and Waseem (2015) analyze responses to notches in the PIT in Pakistan. Bachas and Soto (2015), Carrillo, Emran, and Rivadeneira (2012), and Carrillo, Pomeranz, and Singhal (2014) assess the reactions to incentives in corporate taxation. Most interestingly, the last two papers refer to data in Ecuador and find substantial evidence for tax evasion of firms in the country. As shown by Besley and Persson (2013), however, in the course of their progress towards more formal economies, developing countries rely increasingly on PIT. This lends importance and relevancy to our analysis of a personal income tax system in a developing country in the middle of this transition.

### 3 Institutional Background

Since 2008, Ecuador has implemented a wide range of economic and political reforms. The government has greatly increased spending on social programs and public service delivery. While a surge in oil revenues facilitated some of this increased spending, the tax administration has also pushed wide-ranging reforms of the tax system and tax collection policies. As a result, tax revenue as well as the tax base have grown substantially over the past years. Moreover, there has been a strong increase in the formalization of the economy.

Taxation in Ecuador can be broadly categorized into personal income taxes (PIT), a value-added tax (VAT) of 12 % (food and some other goods are exempt)<sup>3</sup>, corporate taxation (22% of profits since 2013), and a tax on foreign money transfers and special consumption taxes. Figure 1a gives a clear picture of the growth of tax revenue in Ecuador in the past years.<sup>4</sup> Between 2006 and 2015, central government tax revenues have increased from about 10% to almost 14% of GDP and have more than doubled in real terms. One of the main reasons for higher tax revenue is an increase in formalization of the economy and the tax administration's wide-ranging efforts to increase tax compliance.

The government has adopted a number of policies to increase formalization of the economy, the most important of which are extensive deduction possibilities of income tax. Along with 'receipt lotteries', in which citizens have the possibility to submit receipts and win prizes, these policies substantially increase the demand for receipts. Emitting receipts is not only linked to paying more VAT but also to taking part in other aspects of the formal economy such as retaining income tax and social security contributions for employees. The receipts handed in to the authorities are used to cross-check the sales of businesses and fight tax fraud, especially with respect to VAT reporting behavior. Further measures to increase tax compliance include improved information sharing between government agencies.

The general hike in tax revenue in Ecuador is also reflected in a strong increase in the

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<sup>3</sup>Following a large destructive earth quake in 2016 the Ecuadorian government increased the VAT to 14 % for the duration of one year starting in June 2016.

<sup>4</sup>The Ecuadorian economy was completely dollarized in 2000 following extreme hyperinflation.

number of taxpayers subject to personal income taxation. Figure 1b gives an overview of the absolute number of tax declarations submitted. Between 2006 and 2015, the total number of tax declarations for private sector employees increased from 1 Million to about 2.5 Million.

### 3.1 Personal Income Taxes

Ecuador has a unified PIT schedule which is levied on almost all regular sources of wage and self-employed income.<sup>5</sup> Tax liability in Ecuador is individually determined (no family taxation).<sup>6</sup>

The PIT liability is calculated progressively with numerous small jumps in the marginal tax rate, starting at 5% and going up to 35%. In 2008, the government enacted a series of reforms of the tax system, including an increase of the maximum marginal tax rate from 25% to 35%. Figure 2 gives an overview of the marginal tax rates in 2013. The cutoff income levels change yearly according to inflation<sup>7</sup>, the exact values since 2006 are displayed in Table 1.

PIT in Ecuador starts being levied at relatively high levels. In 2013, annual income below 10,180 USD was not charged any income tax. For the same year, the monthly minimum wage is set at 318 USD, corresponding to yearly taxable income of 3,816 USD, well below the first tax bracket. The minimum wage is estimated to be slightly above the median wage and slightly below average wage in Ecuador for 2008 to 2012 (Canelas, 2014). This shows that PIT is only applicable to relatively high-earning individuals in Ecuador.

A uniqueness of the Ecuadorian tax system are the generous deduction possibilities

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<sup>5</sup>Notable exceptions include all forms of payments from the social security system (pension payments, educational stipends, disability benefits, etc.), severance payments, interest on savings accounts, occasional capital gains, returns from investment funds or long-term deposits as well as certain additional wage benefits mandatory under labor market regulations.

<sup>6</sup>Furthermore, employees in the private sector pay 9.35% of their wage income in social security contributions. Paying these social security contributions entitles people to a range of benefits including pensions, health insurance, disability insurance and unemployment benefits. Social security contributions are only levied on regular wage income, not irregular special payments such as boni. Since 2014, the contribution has increased to is 9.45%. The employer pays a slightly larger share of 11.15%, constant over time.

<sup>7</sup>The rate used for inflation adjustments is the yearly change in consumer price index for urban areas published by Ecuador's National Statistics Institute INEC on November 30 of a given year.

for personal expenses in education, health, food, clothing and housing introduced in 2008. The total deductible amount of personal expenses is limited to the smaller of 50% of individual income or 1.3 times the tax-exempt income amount (in 2013 this was  $1.3 \times 10,180 = 13,234$  USD). Each category is individually capped at 0.325 times the tax-exempt income amount, except for health expenditures, which have an upper limit of 1.3 times the tax-exempt amount. To make receipts presentable to the tax authority, they must be issued to the name of the tax payer or his/her dependents and include their unique identification number. One main policy objective of these deduction possibilities is to increase formalization of the economy, as wage earners have an incentive to demand receipts. In order to claim these deductions, taxpayers are legally obliged to keep copies of their receipts. The standard tax declaration form F107 submitted by the firm, however, only contains information on the total yearly amount of personal expenses in each category. If the total value of deductions exceeds a certain reporting threshold, the tax authority asks the taxpayers to additionally submit an online annex with details about the receipts.<sup>8</sup>

The mechanism by which tax declarations and deductions are submitted in Ecuador deserves some special attention and is key to understanding the findings in our analysis. Personal income tax is primarily filed on a firm-reported form (F107, see figure A.3 in the Appendix). This form can only be submitted to the tax authority by the employing firm and includes the level of deductions in personal expenses. In March of each year, wage earners fill out a form with their *projected* expenses in health, education, food, clothing and housing for that whole year and submit it to their employer. Based on these figures, the employer computes the level of the withholding tax for the following year. Workers are given the opportunity to update their information on deductions in October. If an individual claims deductions above the reporting threshold (50% of the tax free amount, or 5090 US\$ in 2013), he must submit the receipts with the unique receipt number via an online annex after the end of the fiscal year<sup>9</sup>. While the ultimate responsibility for the

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<sup>8</sup>From 2008 to 2010, this threshold was \$7500 and since 2011 the tax authority applies the threshold 50% of the tax-free amount (hence 5090 US\$ in 2013).

<sup>9</sup>The fiscal year corresponds to the calendar year.

overall correctness of these deductions lies solely with the employee, this system induces a unique form of third-party reporting of deductions. Recent literature shows that third-party information reporting by firms is a key driver for sustaining high levels of taxation (Kleven, Kreiner, and Saez, 2015).

For the vast majority of employees (87% of our observations), taxes and personal deductions are only reported by the employer. The remaining 13% of all observations additionally submit a self-reported tax declaration (form F102). The primary purpose of this self-reported tax declaration form is to report self-employment income. However, some individuals who additionally submit a self-reported income declaration actually do not report any self-employment income.<sup>10</sup>

## 4 Data and Descriptives

The data we use in this paper results from the merges of several administrative datasets in Ecuador administered by the Ecuadorian tax authority *Servicio de Rentas Internas* (SRI). The core data consist of firm-reported personal income tax returns of regular employees (tax form F107) for the years 2006-2015.

We augment these tax records by two important administrative datasets. First, we use the Ecuadorian civil registry (*Registro Civil*) that provides a range of socio-demographic variables, including the year of birth, highest level of education and gender. Second, we merge the tax returns to the central firm-level registry in Ecuador (*Catastro de RUC*). This registry contains firm-level data on industry affiliation, sector (public or private), time of formation of the firm and place of registry. We end up with detailed matched employer-employee data that allows us to track a given individual's coworkers over time.

A significant fraction of workers has multiple observations per year due to the fact that people have various employers throughout a given calendar year (each employer submits

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<sup>10</sup>In related work, we are analyzing how individuals are using these self-reported tax declaration forms to circumvent their employer and change their level of deductions. Self-employed individuals need to file the self-reported tax declaration with their total income in March of the year following the relevant fiscal year. The exact date depends on the individual identity number and lies in between March 10th and 28th. Self-employed are liable to pay personal income tax on all of their business profits and wage income and have the same deduction possibilities as wage earners. Each summer, they are charged an advance of 50% of the previous year's tax liability.

one declaration per employee). To compute annual earnings we sum up the incomes at different employers for each individual and year. We consider the spell with the highest earnings as the main employer. We deflate all earnings to real 2013 USD values using the consumer price index of the Ecuadorian National Statistics Institute INEC.

For our analysis of tax responses, we exclude all individuals who are employed in the public sector and only focus on private sector employees for two important reasons. First, private sector employees might have better opportunities to adjust their taxable income by bargaining with their employer about the wages and employers in the private sector might provide more support in filing the deductions. Second, public sector employees face different incentives than private sector employees and their pay is often regulated by predetermined government pay scales.

Figure 3 displays the distribution of gross income in Ecuador pooling all observations in our sample from 2006 to 2015. We concentrate on workers who earn at least twelve times the monthly Ecuadorian minimum wage (yearly earnings of  $12 \times 318 = 3,816$  USD in 2013) and those who earn less than 30,000 USD. The individual data is compressed into bins of \$50 and plotted as bin frequencies for each bin. In general, the income distribution is downward sloping, with the most frequent points being around the minimum wage. The graph contrasts the income distribution with the marginal tax schedule, as given by the step function with values on the right vertical axis. The gross income distribution is clearly smooth around all kink points of the marginal tax schedule depicted in the figure.

This is different for taxable income, i.e., gross income minus all deductions, displayed in Figure 4. There is a clear spike in the distribution of taxable income just before the first kink in the marginal tax schedule at 10,180 USD. Evidently, individuals do not change their real labor supply but change the amount of deductions in response to the tax incentives.

While bunching is strong and pronounced at the first jump in the marginal tax schedule, we do not observe any bunching at later kink points. This could be due to the fact that the first kink where an individual starts paying taxes is the most salient. Arguably, due to behavioral biases the first dollar in taxes an individual pays can lead to higher

disutility than further tax payments. Moreover, individuals may perceive a discontinuity in audit probabilities at the threshold of paying taxes and prefer to stay under the radar of the tax authority. In our analysis of bunching behavior in the following section, we therefore focus exclusively on the first kink of the marginal tax schedule.

The difference between Figures 3 and 4 indicates that adjustments in taxable income are entirely driven by reporting behavior. In particular, the introduction of the generous deduction possibilities in Ecuador in 2008 led to a wedge between the number of individuals with *gross* income above the first kink in the tax schedule and those with *taxable* income above the first kink (see Figure 5). Over time, a growing number of individuals avoids paying taxes by adjusting the taxable income. In the following section we quantify the amount of bunching and analyze the determinants of learning about tax avoidance.

## 5 Results

In this section, we present the empirical results from analyzing the individual tax return data in Ecuador. The first part uses the bunching methodology developed by Saez (2010) and Chetty et al. (2011) to estimate the extent of behavioral responses to taxation and documents general learning dynamics. The second and third part of this section analyze the channels through which this learning takes place by focusing on two main mechanisms: adapting to the firm-level practices and learning from co-workers.

### 5.1 Tax Bunching

To quantify the amount of bunching at the first kink of the marginal tax schedule, we draw on the methods laid out in Saez (2010) and Chetty et al. (2011). Using binned income data (50\$ bin size), we estimate a counterfactual density (polynomial of degree 5) around the kink that would prevail in the absence of the kink and compute the difference between the actual density and the counterfactual density.<sup>11</sup> Figure 6 displays the distribution of taxable income around the kink. The empirical density is represented by the blue dots

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<sup>11</sup>Sensitivity checks varying the bin width, the parametric form of the polynomial and the bunching window left out in the estimation of the counterfactual density are available on request.

and the estimated counterfactual is represented by the red line. The estimate for the excess mass is highly significant and very large, indicating that more than three times as many individuals are located around the kink compared to the expected mass under the counterfactual of no kink.

Table 2 displays the estimated excess mass separately for each year in the sample period. We find positive and significant bunching in taxable income and over time the estimates of the excess mass increase strongly from 1.36 in 2006 to 6.03 in 2015. In 2006 and 2007, before the introduction of the deduction possibilities, our bunching estimates in taxable income are identical to those of gross income. Starting in 2008, however, bunching in taxable income increases strongly while we do not observe significant bunching in gross income anymore.

To analyze whether the overall increase in tax bunching in Ecuador is driven by experience in filing taxes we construct a specific experience measure. Our measure of experience with the tax system keeps track of whether individuals have earned more than the tax exempt threshold in the previous two years. This measure is important since only individuals who earn more than the income threshold of the first kink have an incentive to learn about deduction possibilities in order to avoid paying taxes.

Figure 7 depicts and quantifies the amount of tax bunching for individuals with and without recent exposure to the tax system. In Panel (a) we observe that individuals who have not had any gross income above the first kink of the marginal tax schedule in the previous two years show rather low levels of bunching. Those individuals with at least one year of gross income above the first kink in the previous two years, however, show much stronger stronger levels of bunching. The mass in the vicinity of the kink is estimated to be 6.171 times higher than the counterfactual.

One major concern in comparing bunching estimates between these two subgroups is that they may be selected with regard to income and other socio-demographic factors.<sup>12</sup> To address this issue, we measure the effect of our experience measure on tax-adjustment behavior while holding other factors such as income levels fixed. Table 3 presents re-

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<sup>12</sup>This is partly already mitigated by the fact that the bunching estimator is a local estimator measuring the excess mass only for the specific sample at hand.

sults from simple probit regressions with an indicator for bunching, defined as having taxable income within the range of 1000\$ to the left of the tax-exempt threshold, as the outcome variable. We restrict the sample to individuals in the years 2008 - 2015 with gross income above the kink but still within the relevant range for bunching using the deduction possibilities. Column (1) of Table 3 shows that our measure of experience with the tax system (defined as having earned more than the tax exempt threshold in the previous two years) has a positive and significant effect on individual bunching behavior. More importantly, column (2) illustrates that even when controlling for gross income and a range of individual and firm-level control variables, the size, direction and significance of the experience effect remains comparable. The regression furthermore provides insight into which demographic characteristics are important in determining whether a given taxpayer bunches. Woman and married individuals are more likely to bunch, and interestingly higher levels of education lead to a higher propensity to bunch.

The evidence presented in this section strongly supports the hypothesis of learning dynamics in tax bunching at the kink. In order to gain a more detailed understanding of the mechanisms that underlie the dynamic patterns, we investigate a sample of job switchers as well as individuals with changes in their co-worker composition in the next subsections.

## 5.2 Job Switchers

For our sample of job switchers, we consider all job transitions of individuals who switch their main employer between 2010 and 2014.<sup>13</sup> In the case of multiple moves of one worker in this period, we only consider the first move.<sup>14</sup> In order to have balanced observations for the event study outlined below, we only keep job switchers where we are able to observe at least two consecutive years before and after the move at the respective firm of origin and destination.

We classify the firm of the job switchers into quintiles based on the coworker bunching

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<sup>13</sup>In case of multiple employers we consider the main employer as the one with the highest earnings. The year of move is the first year in which the main employer of an individual has changed.

<sup>14</sup>In a robustness check, we also analyze the sample of movers who move only once with no change in the results.

shares in their origin and destination firm. In particular, based on the sample of all private sector employees with gross earnings between 5000 and 25000 USD<sup>15</sup> in a given year, we compute the distribution of the share of co-workers who bunch and split the sample into quintiles. For each move, we can then assign the origin firm as well as the destination firm to one of the quintiles for the respective years.

Summary statistics for the full sample of job switchers are reported in the first column of Table 4. On average, an individual who changed jobs is 32 years old. 46% of the movers are married, 30% are female, and 25% of the movers have some kind of tertiary education. The average move is related to a substantial raise in wages as the mean gross income increases from about \$6100 to about \$6700. Similarly, taxable income increases from \$5660 to \$6200. The share of workers who file deductions also increases (from 8% to 10%).

Using an event study graph, we observe the dynamic adjustment process of individuals depending on the quintile they are moving to. Figure 8 plots the share of bunchers in taxable income, defined as those who report taxable income in a \$1000 window to the left of the kink, among workers starting from a firm in the middle quintile of the bunching share distribution. The horizontal axis indicates the year relative to the move where year zero is the first year at the new firm. The data show a clear asymmetric pattern of adjustment. The share of bunchers among workers who move to a high-bunching firm sharply increases after the move with an especially strong increase in the second year at the new firm, resulting in the bunching share more than doubling its pre-move level. In contrast, the share of bunchers among workers moving to mid- or low-bunching firms both have a general upward trend in the years after the move. However, this upward trend is magnitudes smaller than the increases among individuals moving to a high bunching environment.<sup>16</sup>

Figure 8 indicates parallel and stable pre-move trends between individuals moving to

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<sup>15</sup>By restricting our sample to this subset, we guarantee that we only take into account those coworkers that are close enough to the first kink for bunching to be a viable option.

<sup>16</sup>Table A.2 in the appendix depicts the same event-study graph for individuals starting in the low or high quintile of the bunching distribution. In both alternative samples we also find a much stronger increase in the share of bunchers among individuals moving to the top quintile than among individuals moving to the mid or low quintile.

firms in different parts of the bunching share distribution. This lends credibility to the parallel trends assumptions in standard difference-in-differences type analyses. However, columns 2-4 of Table 4 show that job switchers to low-, middle-, and high-bunching firms might be selected in terms of observable pre-move characteristics. In order to address possible selection issues, we employ three differing identification strategies that quantify the magnitude and significance of the effects of switching a job while controlling for individual unobserved heterogeneity as well as a number of time varying individual characteristics such as earnings before and after the job switch.

The main idea of the first identification strategy is to compare job switchers starting in a firm in the mid quintile of the bunching distribution and moving to a firm in the high quintile to those starting in the mid quintile and moving to a firm in the same quintile. We apply the same approach to individuals moving to a firm in the low quintile of the bunching distribution. For each destination quintile  $\in \{low, high\}$ , we separately estimate the following regression on the subsample of individuals starting in a firm in the mid quintile and moving to the respective destination quintile:

$$Y_{it} = \beta_0 + \sum_{k=-2}^{k=2} \gamma_k D_{it}^k + \delta post_{it} \times quintile_i + \theta X_{it} + \lambda_t + \alpha_i + \epsilon_{it}. \quad (1)$$

The dependent variable is an indicator equal to one if individual  $i$  has taxable income within a \$1000 window to the left of the kink at time  $t$ . We include event-time dummies  $D_{it}^k = \mathbb{1}[t = k]$  indicating the respective year relative to the job switch (with  $k = 0$  being the first year at the new firm) in order to control for any general trends occurring in event time. The indicator variable  $post_{it}$  takes on the value of one in the years after the job switch and  $quintile_i$  takes on the value of one if an individual moved to a high or low quintile respectively.  $X_{it}$  are worker and firm characteristics, including gross earnings, age squared, firm size, industry classification and an indicator for corporate firm status. We further include individual ( $\alpha_i$ ) and time ( $\lambda_t$ ) fixed effects. The coefficient  $\delta$  measures

the general effect of moving to a high or low bunching firm respectively.<sup>1718</sup>

The estimates are displayed in Panel A of Table 5. Columns (1) and (3) are without and columns (2) and (4) with the individual and firm-level controls  $X_{it}$ . The results confirm very strong firm-level effects on individual tax adjustment behavior: moving to a high quintile firm increases bunching by more than 3 percentage points while moving to the low quintile has no significant effect (particularly when controlling for time-varying worker and firm characteristics).

In a second model, we explicitly look at the timing of the effects by estimating separate coefficients for each period relative to the move. Particularly, we modify the equation to

$$Y_{it} = \beta_0 + \sum_{k=-2}^{k=2} \gamma_k D_{it}^k + \sum_{k=-2}^{k=2} \delta_k D_{it}^k \times \text{quintile}_i + \theta X_{it} + \lambda_t + \alpha_i + \epsilon_{it} \quad (2)$$

where the coefficients  $\delta_k$  on the interaction term measure the anticipatory and post treatment effects reported in Panel B of Table 5. Differentiating the effect by year relative to the job switch we find no anticipatory effects before the job switch throughout the samples. The effects accruing to moves to a high bunching environment are persistent and strongest in the second year after the move. In contrast, moving to a lower bunching environment has no significant effect in any year after the move.

In our third specification, we restrict the sample to those individuals who switched to a high or low bunching environment and identify the effects only through the timing of the move. We do not employ a comparison group anymore. Specifically, we run the following regression:

$$Y_{it} = \beta_0 + \sum_{k=-1}^{k=2} \gamma_k D_{it}^k + \theta X_{it} + \lambda_t + \alpha_i + \epsilon_{it} \quad (3)$$

with the variables as defined above. In order to rule out any compositional effects, we furthermore restrict the sample in this regression to only include observations from the

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<sup>17</sup>In a sensitivity check, we estimate this same regression without individual fixed effects but instead a wide range of individual specific demographic controls (age, gender, education) and find no substantial difference in the results.

<sup>18</sup>We furthermore estimate the same regression without the  $D_{it}^k$  event-time indicators and find no substantial change in the direction of the results.

two years before and after the move for which we have a perfectly balanced panel. Panel C of Table 5 presents the results of these additional regressions. We find very similar results to before and take this as further evidence for the robustness of our findings.

In summary, the asymmetry in the adjustments after moves into the different quintiles points towards workplace or firm driven knowledge effects. In particular, moving to an environment with a higher share of coworkers who bunch has a learning effect and increases the likelihood to bunch. This effect is persistent and strongest in the second year after the job switch. On the contrary, moving to an environment with a lower share of bunchers does not change an individual's behavior and thus is consistent with a memory effect.

The asymmetric response to firm-level bunching confirms the finding of knowledge effects in Chetty et al. (2013). They analyze moves of self-employed individuals between regions and find asymmetric responses that are also consistent with learning and memory. In particular, self-employed workers who move to a region with a high share of bunchers increase their bunching while there is no effect for movers to low-level regions.

In order to lend credibility to our results we have conducted a number of robustness checks and alternative specifications. Table A1 in the Appendix shows the results from regression equation (1), however, here restrict the sample to those individuals with gross income in a range where they can use their deductions to bunch at the first kink of the marginal tax schedule. Even though the sample is smaller, we find no changes in the results. If anything, the magnitude of the effects is larger.

### 5.3 Co-worker Learning

The previous section on job switchers documents that firms seem to be a key driver for individual bunching behavior. Individuals learn about tax adjustment opportunities from their firms. However, this learning could be driven both through learning directly from the firm or learning from co-workers. In order to disentangle these two learning mechanisms from each other, we look specifically at how individuals respond to possible information flows provided by their co-workers. We do not find evidence for individuals

learning about tax-adjustment opportunities through changes in the composition of their co-workers.

We quantify this co-worker learning channel by looking at individuals with recent changes to their co-worker composition. Specifically, we construct a sample of firms with incoming employees who were potential bunchers<sup>19</sup> due to their gross income in the year before joining the new firm. We only consider firms hiring new workers once in the years 2010-2014 and in which we can observe at least two years before (2008 and 2009) and two years after (2014 and 2015) the event. These restrictions provide a sample balanced in event time and allow us to abstract from various treatments happening sequentially.

Among these firms with incoming potential bunchers, we divide the new employees into those that reduced their taxable income to just below the first kink (“bunchers”)<sup>20</sup> and those that did not in the year *before* joining the new firm. We use this distinction to classify firms into “treatment” (receiving bunchers) and “control” (receiving non-bunchers) groups.

Table 6 provides descriptive statistics for the workers in this sample of firms. Along key demographic variables (average age, share married, share female, share tertiary education) treatment and control groups are very similar. Furthermore, average firmsize between the two groups (58 and 61 employees) is very similar. There are some differences in terms of wages and tax-filing behavior in the year before the arrival of new co-workers.

Using a similar event study methodology as employed in Section 5.2, we plot average leave-out bunching levels in treatment and control firms relative to the year of the move. A given firm’s leave-out bunching share disregards the new co-worker and only calculates the share of bunchers among the original co-workers. The results in Figure 9 suggest that, while workers in treatment firms tend to have higher bunching shares throughout the whole sample period, their tax adjustment behavior does not change substantially after the arrival of a buncher.

We conduct the same event study for subsamples in which we suspect the influence to

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<sup>19</sup>We define potential bunchers as individuals with gross earnings in a range allowing them to lower their taxable income below the first kink of the tax schedule by using deductions. In 2013 real USD, this was gross earnings between 10180 and 20360 USD.

<sup>20</sup>We again take at an interval of 1000 USD to the left of the first kink.

be stronger. Figure 10 depicts firms which had no bunchers before the incoming worker and Figure 11 small firms (less than 25 employees). In both of these cases our original finding of no effect is confirmed.

Table 7 provides regression results for the previous graphic evidence. With the aim of addressing possible selection issues and quantifying the magnitude of the effects, we mirror the identification strategies employed in Section 5.2. Specifically, we estimate

$$Y_{it} = \beta_0 + \sum_{k=-2}^{k=2} \gamma_k D_{it}^k + \delta post_{it} \times treat_i + \theta X_{it} + \lambda_t + \alpha_i + \epsilon_{it}. \quad (4)$$

where  $i$  now refers to a given firm and not an individual.  $Y_{it}$  is the leave-out bunching share among the incumbent co-workers,  $D_{it}^k$  are indicators for event time,  $post_{it}$  is an indicator for an observation being after the incoming co-worker,  $treat_i$  is an indicator for a firm receiving an incoming buncher. We include firm ( $\alpha_i$ ) and time ( $\lambda_t$ ) fixed effects and in  $X_{it}$  we control for firm size as well as employee characteristics (average income, share tertiary educated, average age, share married, and share female).

In a similar identification approach, we separate the overall effect into individual time components by estimating the following regression:

$$Y_{it} = \beta_0 + \sum_{k=-2}^{k=2} \gamma_k D_{it}^k + \sum_{k=-2}^{k=2} \delta_k D_{it}^k \times treat_i + \theta X_{it} + \lambda_t + \alpha_i + \epsilon_{it}. \quad (5)$$

In this regression the coefficients  $\delta_k$  measure the anticipatory and post treatment effects. These coefficients, along with the estimate for the overall effect from equation (4), are reported in Table 7. Among all three samples there do not seem to be any effects of the change in co-worker composition on individual tax-adjustment behavior.<sup>21</sup> We conclude these findings with the observation that learning about tax adjustment opportunities seems to be more likely driven through firm-level effects than through learning from co-workers.

The observation that firms are the main drivers of individual bunching naturally

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<sup>21</sup>In unreported results we additionally identify the effect of co-workers within the sample of treated firms purely through the timing of the effect akin to the regression strategy in equation (3). We do not find robust evidence for any effects.

leads to the question of characterizing those firms whose employees are most likely to bunch. The following regression results in Table 8 show correlations between the share of bunchers in a given firm (among potential bunchers in the respective firm) and various firm-level characteristics and aggregate demographic characteristics of the employees. We see that larger firms tend to have smaller bunching shares. The sectors (industry classification) seem to play an important role in characterizing a given firm's bunching share. The reported coefficients compare a given industry with the omitted category, in this case agriculture, livestock and mining. Indeed a number of these sector coefficients go into the expected direction. Sectors with strong connections to the public sector (electricity, gas and water as well as health and social services) are related to low firm-level bunching shares.<sup>22</sup> The strongest positive coefficient is given by firms operating in the financial sector, as we can expect these (and their employees) to be most knowledgeable in adjusting their taxable income.

## 6 Conclusion

In this paper we analyze bunching in personal income taxes using new administrative tax-return data from Ecuador. Learning seems to play an important role in determining how individuals adjust their taxable income: people with experience and exposure to the tax system are more likely to position their taxable income within the vicinity of the first kink of the marginal tax schedule. The main margin of adjustment of taxable income lies in the reporting of generous deduction possibilities. We do not find evidence for true economic adjustments such as labor supply responses. Moreover, by exploiting data on individuals switching their jobs, we find strong bunching spillovers at the firm level. Someone moving from a mid-bunching environment to a high-bunching environment increases their probability to bunch by 3-5 percentage points. In contrast, for someone switching to a low bunching environment, we find almost zero effect on their probability of bunching. These asymmetric effects lead us to believe that knowledge seems to be the

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<sup>22</sup>Note that these results pertain only to firms in the private sector as public sector firms were excluded throughout the analysis.

main driver in these spillover effects at the firm level.

Apart from establishing the importance of knowledge in individual tax adjustment behavior, we constrast a further channel of information transmission: co-worker learning. By studying firms which recently hired employees we look at how incoming bunchers affect their co-workers' tax-filing behavior. We find no evidence for incumbent employees learning from their new co-workers' behavior, even among small firms or firms without any previous bunchers. We conclude that firms, not co-workers, seem to be the main driver of tax adjustment behavior.

From a policy perspective, these findings on how taxpayers in a low-enforcement setting learn about tax adjustment and avoidance opportunities are highly relevant. A range of developing and middle-income countries have recently undergone numerous reforms aiming towards the formalization of the economy. While designing these reforms it is important to take into account how new taxpayers react to the incentives provided by the tax system over time. Our analysis has shown that firms play an important role in how knowledge about tax adjustment opportunities is spread. In devising strategies to combat tax avoidance and increase revenue, this is an important fact to keep in mind.

In future research on behavioral responses to taxation, we think it is important to focus more strongly on dynamic aspects, especially taking into account that individuals learn over time about the incentives given by the tax system. In our analysis we show that firm-level effects play an extremely important role in determining individual tax-filing behavior. In future research, it would be of great interest to quantify the role of firms in tax filing and possibly tax avoiding behavior of individuals.

## Bibliography

Pierre Bachas and Mauricio Soto. Not(ch) your average tax system: Corporate taxation under weak enforcement. Technical report, UC Berkeley, 2015.

Spencer Bastani and Håkan Selin. Bunching and non-bunching at kink points of the swedish tax schedule. *Journal of Public Economics*, 109:36–49, 2014. URL <http://www.sciencedirect.com/science/article/pii/S0047272713001916>.

Timothy J Besley and Torsten Persson. Taxation and development. *Handbook of Public Economics*, 5:51–110, 2013.

Michael Best, Anne Brockmeyer, Henrik Jacobsen Kleven, Johannes Spinnewijn, and Mazhar Waseem. Production vs revenue efficiency with limited tax capacity: Theory and evidence from pakistan. *Journal of Political Economy*, 123(6):1311–1355, 2015.

Carla Canelas. Minimum wage and informal in ecuador. Technical report, UNU-WIDER Working Paper, 2014.

Paul Carrillo, M. Shahe Emran, and Anita Rivadeneira. Do cheaters bunch together? profit taxes, withholding rates and tax evasion. Technical report, Working Paper, 2012.

Paul Carrillo, Dina Pomeranz, and Monica Singhal. Tax me if you can: Evidence on firm misreporting behavior and evasion substitution. Technical report, Working Paper, 2014.

Raj Chetty and Emmanuel Saez. Teaching the tax code: Earnings responses to an experiment with eitc recipients. *American Economic Journal: Applied Economics*, 5(1):1–31, 2013. URL <http://www.ingentaconnect.com/content/aea/aej/2013/00000005/00000001/art00001>.

Raj Chetty, John Friedman, Tore Olsen, and Luigi Pistaferri. Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from danish tax records. *Quarterly Journal of Economics*, 126(2):749–804, 2011.

- Raj Chetty, John N Friedman, and Emmanuel Saez. Using differences in knowledge across neighborhoods to uncover the impacts of the eitc on earnings. *American Economic Review*, 103(7):2683–2721, 2013. URL <http://www.nber.org/papers/w18232>.
- Henrik J Kleven and Mazhar Waseem. Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from pakistan. *The Quarterly Journal of Economics*, 128:669–723, 2013. URL <http://qje.oxfordjournals.org/content/early/2013/04/05/qje.qjt004.abstract>.
- Henrik J Kleven, Claus T Kreiner, and Emmanuel Saez. Why can modern governments tax so much? an agency model of firms as fiscal intermediaries. Technical report, Working Paper, 2015.
- Henrik Jacobsen Kleven. Bunching. *Annual Review of Economics*, 8(1):435–464, 2016. URL <http://dx.doi.org/10.1146/annurev-economics-080315-015234>.
- Jörg Paetzold and Hannes Winner. Taking the high road? compliance with commuter tax allowances and the role of evasion spillovers. Technical report, 2014.
- Emmanuel Saez. Do taxpayers bunch at kink points? *American Economic Journal: Economic Policy*, pages 180–212, 2010.

Table 1: Tax Brackets (in US \$)

Marginal Rate	06	07	08	09	10	11	12	13	14	15
5%	7,680	7,850	7,850	8,570	8,910	9,210	9,720	10,180	10,410	10,800
10%	15,360	15,700	10,000	10,910	11,350	11,730	12,380	12,970	13,270	13,770
12%	–	–	12,500	13,640	14,190	14,670	15,480	16,220	16,590	17,210
15%	30,720	31,400	15,000	16,370	17,030	17,610	18,580	19,470	19,920	20,670
20%	46,080	47,100	30,000	32,740	34,060	35,210	37,160	38,930	39,830	41,330
25%	61,440	62,800	45,000	49,110	51,080	52,810	55,730	58,390	59,730	61,980
30%	–	–	60,000	65,480	68,110	70,420	74,320	77,870	79,660	82,660
35%	–	–	80,000	87,300	90,810	93,890	99,080	103,810	106,200	110,190

Note: Columns denote the years to which the tax brackets apply. The numbers indicate the value of the lower bound above which income is taxed at the relevant marginal rate. For example: In 2014, all income between 10,410 USD and 13,270 USD is taxed at the marginal rate of 5%.

Table 2: Bunching estimates over time

	pooled	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Taxable Income	4.13*** (0.24)	1.36*** (0.37)	1.86*** (0.36)	2.88*** (0.49)	1.81*** (0.61)	3.34*** (0.54)	3.88*** (0.58)	4.44*** (0.72)	4.63*** (0.91)	5.18*** (0.77)	6.03*** (0.61)
Gross Income	0.23 (0.29)	1.35*** (0.38)	1.85*** (0.36)	1.16** (0.59)	-0.36 (0.81)	1.05 (0.75)	0.80 (0.75)	0.26 (0.94)	-0.36 (1.04)	-0.62 (0.99)	-0.33 (0.79)

Note: This table reports bunching estimates for taxable and gross income by year and in the pooled sample. The estimates are based on binned income data (50\$ bin size) and a counterfactual density using a polynomial of degree 5. Standard errors reported in parentheses, significance levels are given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

Table 3: Bunching Individuals

	(1)	(2)
Income Experience	0.0828*** (0.0119)	0.0666*** (0.0136)
Gross Income		0.0000242*** (0.00000223)
Age		0.00626*** (0.00226)
Female		0.114*** (0.0113)
Foreign		-0.00962 (0.0173)
Married		0.0454*** (0.00816)
Secondary Education		0.0346* (0.0197)
Tertiary Education		0.0600** (0.0280)
Observations	1069607	1050694

The table shows results from a probit regression with a binary indicator for bunching individuals as dependent variable. The sample is restricted to potential bunchers in 2008 to 2015. Further (unreported) control variables include age squared as well as firm-level control variables such as industry affiliation, firm size, province, firm age and corporate firm indicator. Year fixed effects are included. Standard errors (in parentheses) are clustered at the firm level. Significance levels given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

Table 4: Job Switchers - Descriptives

	<b>Descriptive Statistics</b>			
	(1)	(2)	(3)	(4)
	Full Sample	Mid to Low	Mid to Mid	Mid to High
<b>Demographics</b>				
Age	32.29	33.27	31.27	30.75
Married	0.46	0.47	0.45	0.46
Female	0.30	0.30	0.28	0.31
Tertiary Education	0.25	0.23	0.20	0.27
<b>Pre-Move</b>				
Gross Income	6092.72	5868.99	6278.32	6703.97
Taxable Income	5662.10	5493.57	5838.80	6232.53
Share Deduction Filers	0.08	0.07	0.07	0.08
Buncher	0.04	0.02	0.02	0.04
<b>Post-Move</b>				
Gross Income	6733.50	5115.60	7037.30	7450.82
Taxable Income	6190.15	4854.24	6483.60	6748.53
Share Deduction Filers	0.10	0.06	0.09	0.14
Buncher	0.04	0.02	0.04	0.06
Observations	152617	5919	6717	5682

*Notes:* This table reports summary statistics for the job switcher sample, consisting of all individuals who switch their job between 2010 and 2014 (regarding only their first move) and for whom it is possible to observe at least two consecutive years before and after the move. Pre-move gives mean values in the year before the move, post-move the respective values in the first year at the new firm. Individuals are grouped into quintiles depending on their coworker bunching shares for any given year. Columns (2) to (4) represent individuals starting in the mid (third) quintile of the bunching distribution in the year before the move and moving to a firm in the low (first), mid (third) or high (fifth) quintile.

Table 5: Job Switchers

	(1)	(2)	(3)	(4)
	Mid to Low		Mid to High	
<b>Panel A: Overall Effect</b>				
After event year	-0.00774**	-0.00188	0.0356***	0.0314***
	(0.00386)	(0.00405)	(0.00485)	(0.00473)
<b>Panel B</b>				
<i>Anticipatory Effects</i>				
Event year - 2	0.00350	0.00332	0.00417	0.00333
	(0.00519)	(0.00519)	(0.00559)	(0.00562)
Event year - 1	0.00408	0.00525	0.00534	0.00408
	(0.00546)	(0.00542)	(0.00616)	(0.00612)
<i>Post Treatment Effects</i>				
Event year	-0.00906	-0.00274	0.0185**	0.0148*
	(0.00591)	(0.00597)	(0.00779)	(0.00765)
Event year + 1	-0.00288	0.00349	0.0544***	0.0488***
	(0.00666)	(0.00690)	(0.00790)	(0.00787)
Event year + 2	-0.000188	0.00561	0.0494***	0.0435***
	(0.00838)	(0.00838)	(0.0101)	(0.0100)
Observations	65224	65186	64504	64473
<b>Panel C: Timing</b>				
Event year - 1	-0.00272	-0.00130	-0.00212	-0.00578
	(0.00327)	(0.00544)	(0.00409)	(0.00767)
Event year	-0.00238	0.00634	0.0245***	0.0165
	(0.00337)	(0.00931)	(0.00613)	(0.0144)
Event year + 1	0.0132***	0.0212	0.0699***	0.0541**
	(0.00450)	(0.0137)	(0.00595)	(0.0231)
Controls	No	Yes	No	Yes
Observations	23560	23542	22676	22662

The panels of this table denote the results from regression equations (1), (2) and (3) respectively. Standard errors (in parentheses) are clustered at the destination firm by year level. Significance levels are given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

Table 6: Co-worker Learning - Descriptives

	(1)	(2)	(3)
	Full Sample	Control	Treatment
<b>Demographics</b>			
Avg. Age	35.87	35.88	35.81
Share Married	0.51	0.51	0.52
Share Female	0.37	0.36	0.39
Share Tertiary Education	0.32	0.32	0.33
Firmsize	58.68	58.27	61.35
<b>Pre-Event</b>			
Avg. Gross Income	7143.18	7018.27	7939.66
Avg. Taxable Income	6396.51	6301.83	7000.20
Share Deduction Filers	0.13	0.13	0.17
Share Taxable Income Buncher	0.06	0.05	0.08
Observations	3526	3048	478

Notes: This table shows descriptive statistics for the sample of firms used in the co-worker analysis. Control refers to firms receiving incoming potential bunchers that did not bunch and treatment refers to firms receiving incoming potential bunchers that did bunch in the year prior to joining their new firm. Pre-event refers to the year before the arrival of new co-workers.

Table 7: Co-worker Learning - Regression Results

	All		No Bunchers		Small Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Overall Effect</b>						
DiD estimate	0.0248 (0.0199)	0.0258 (0.0199)	0.0336 (0.0325)	0.0252 (0.0338)	0.0237 (0.0430)	0.0237 (0.0431)
<b>Anticipatory Effects</b>						
Event year - 2	0.0137 (0.0309)	0.0186 (0.0311)	0.0136* (0.00827)	0.0100 (0.00952)	0.0263 (0.0631)	0.0406 (0.0640)
Event year - 1	-0.000354 (0.0324)	0.00374 (0.0326)	0.0136* (0.00827)	0.00921 (0.0102)	-0.0184 (0.0648)	-0.00190 (0.0657)
<b>Post Treatment Effects</b>						
Event year	0.00421 (0.0308)	0.00601 (0.0309)	0.00331 (0.0336)	-0.00726 (0.0348)	-0.0277 (0.0648)	-0.0155 (0.0659)
Event year + 1	0.0480 (0.0334)	0.0540 (0.0336)	0.0842 (0.0531)	0.0737 (0.0544)	0.0731 (0.0731)	0.0874 (0.0735)
Event year + 2	0.0447 (0.0391)	0.0516 (0.0392)	0.0478 (0.0607)	0.0340 (0.0608)	0.0406 (0.0855)	0.0491 (0.0859)
Controls	No	Yes	No	Yes	No	Yes
Observations	11579	11574	2595	2590	4731	4731

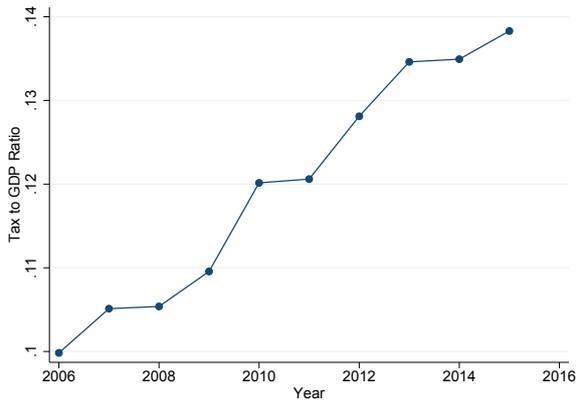
The table reports results from regression equations (4) and (5) at the firm level. Outcome variable is the leave-out bunching share and event year refers to the year of incoming employees. Firm and year fixed effects are included throughout. We control for average income, share tertiary educated, average age, share married, share female and firmsize. Standard errors (in parentheses) are clustered at the firm level. Significance levels are given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

Table 8: Bunching Firms

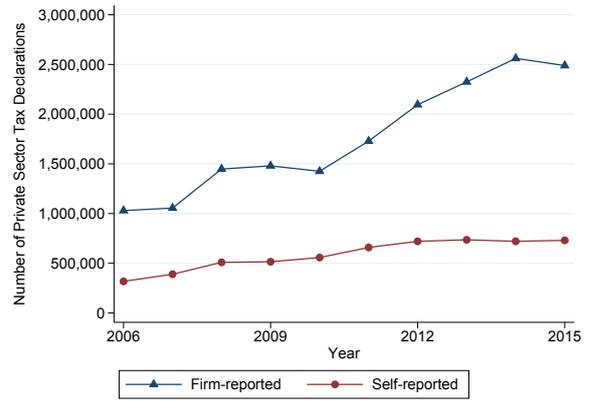
	Share of Bunchers in Firm	
Share Married	0.00957**	(0.00418)
Mean Age	0.00193**	(0.000857)
Share Female	0.0341***	(0.00326)
Between 10 and 100 Employees	-0.0260***	(0.00300)
Between 100 and 1000 Employees	-0.0774***	(0.00787)
More than 1000 Employees	-0.127***	(0.0103)
Corporate Firm	-0.0237***	(0.00304)
<b>Sectors</b>		
Manufacturing	0.0178***	(0.00166)
Electricity, gas and water	-0.00690***	(0.00179)
Construction	0.0180***	(0.00152)
Trade; Repairing	0.0187***	(0.00244)
Hotel and Restaurant	0.0117***	(0.00171)
Transport, Storage, Communication	0.00741**	(0.00241)
Financial Sector	0.0283***	(0.00253)
Real Estate, Business and Renting	0.0159***	(0.00204)
Education	0.00577**	(0.00212)
Health and Social Services	-0.0115***	(0.00220)
Other	0.00526**	(0.00217)
Observations	126540	

The table reports results from an OLS regression at the firm level with the share of bunching individuals in a firm as the dependent variable. Sample and share of bunchers constructed using only potential bunchers in 2008 to 2015. Further (unreported) control variables include average age squared, share secondary and tertiary education, share foreign workers, average number of jobs among workers and firm age. Year and province fixed effects are included. The agriculture, livestock and mining sector is the omitted category. Standard errors (in parentheses) are clustered at the industry level. Significance levels are given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

Figure 1: Formalization

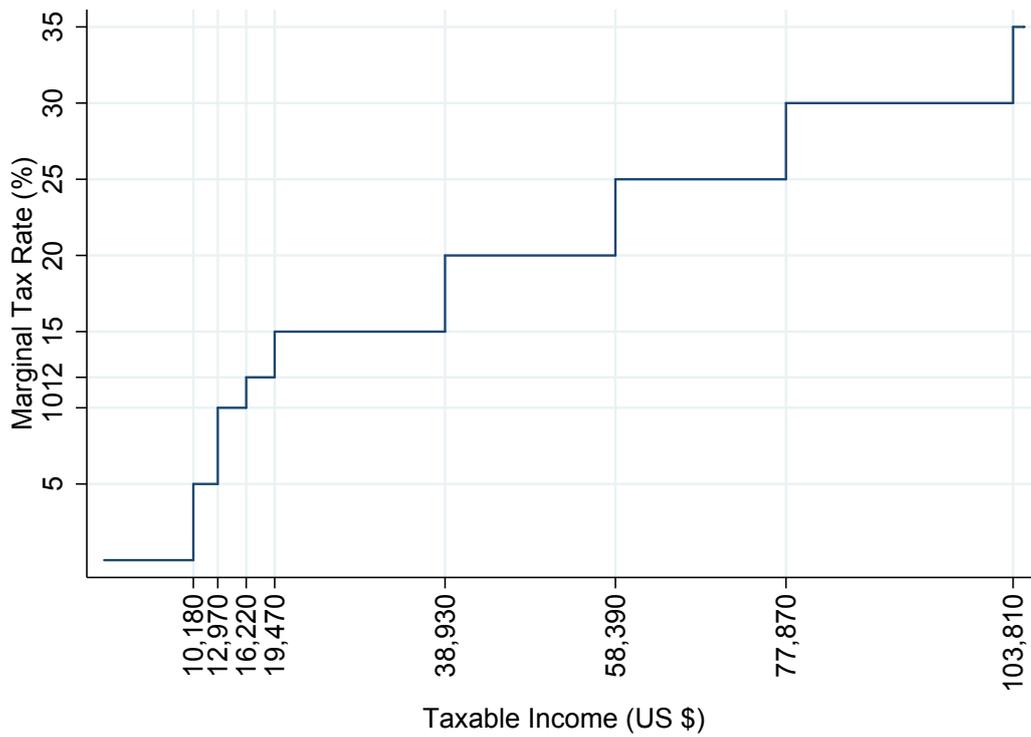


(a) Tax Revenue to GDP



(b) Number of Tax Declarations

Figure 2: Marginal Tax Rates 2013



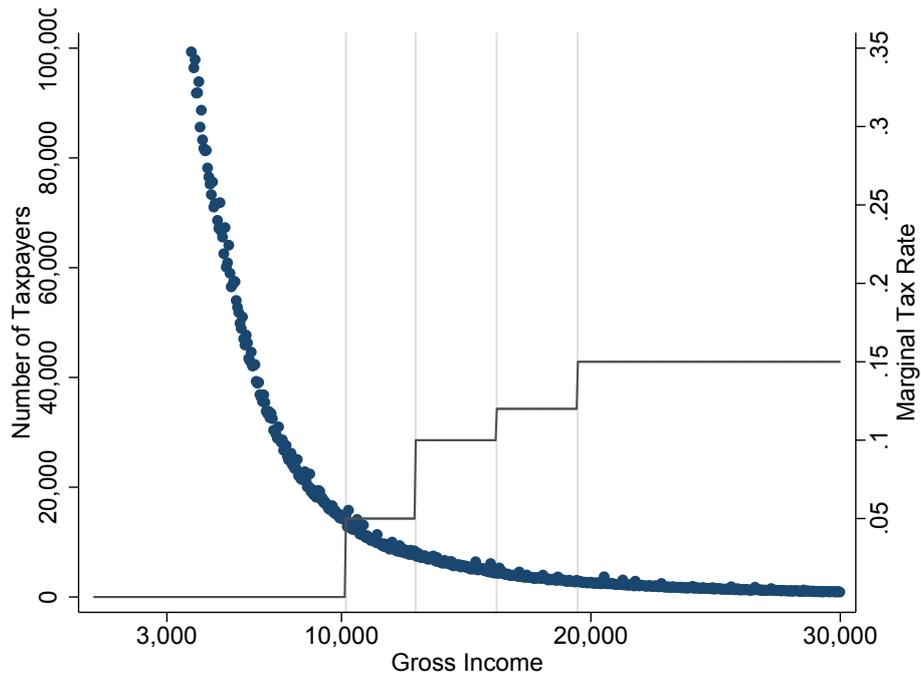


Figure 3: Binned Gross Income

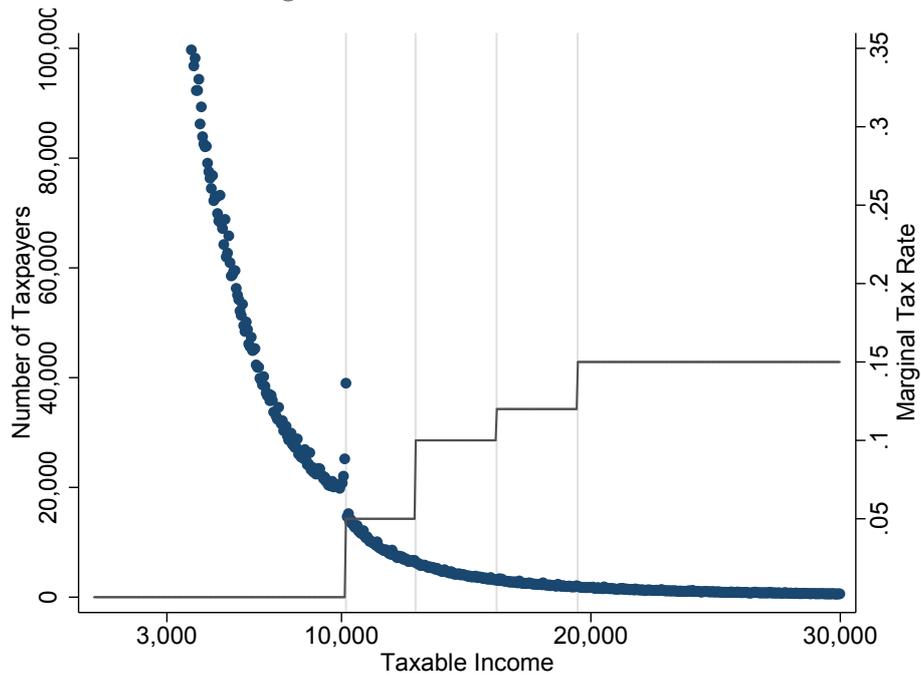
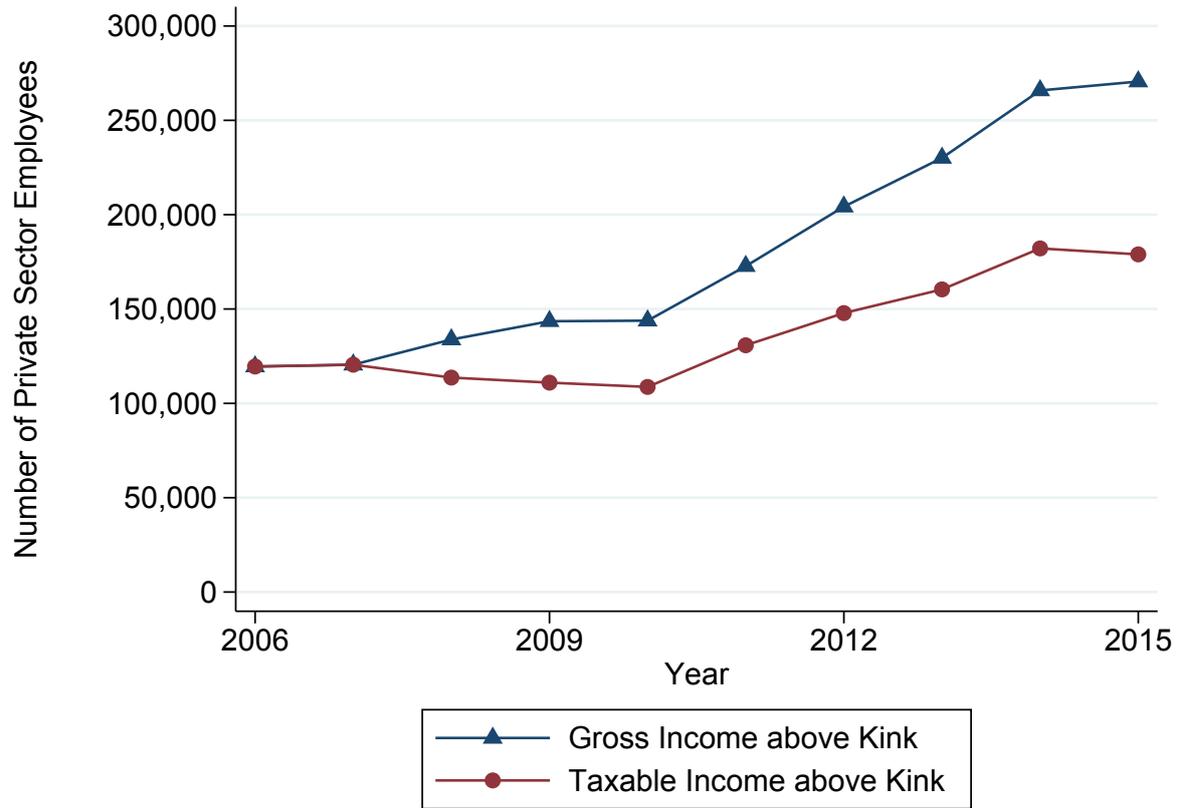


Figure 4: Binned Taxable Income

Figure 5: Number of Employees



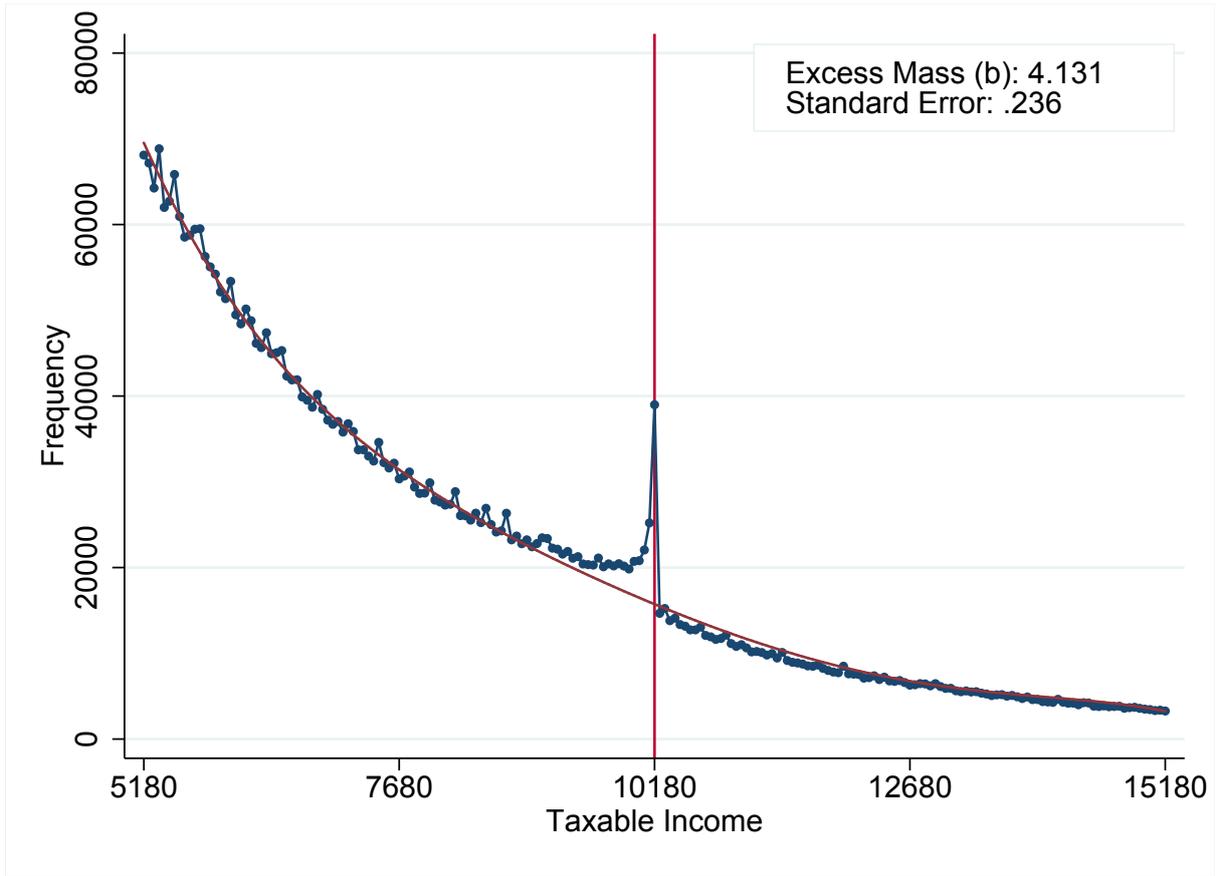
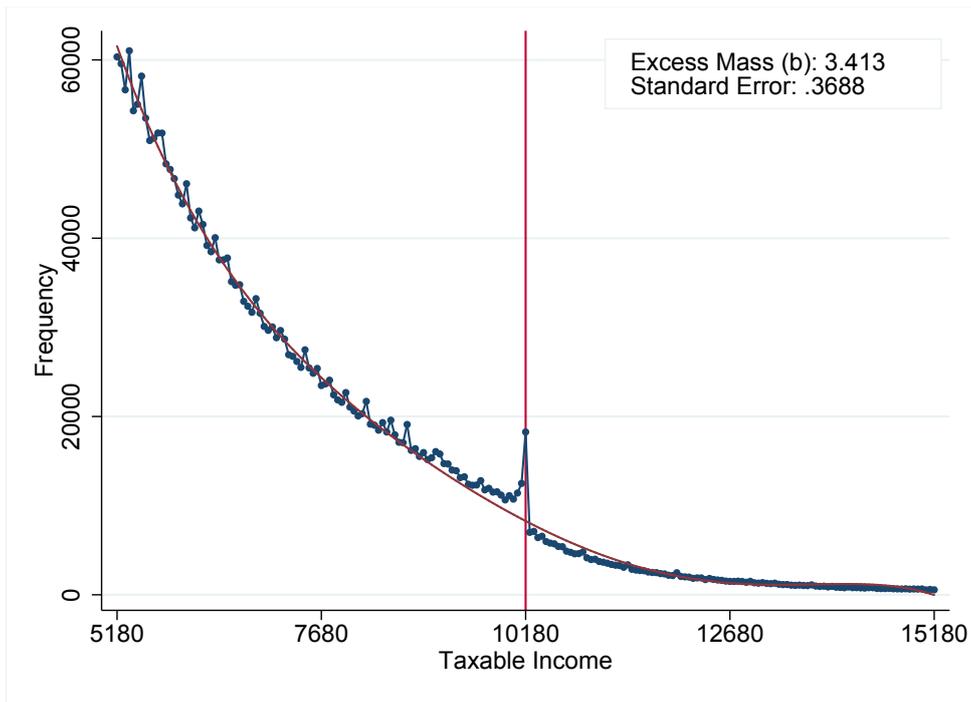
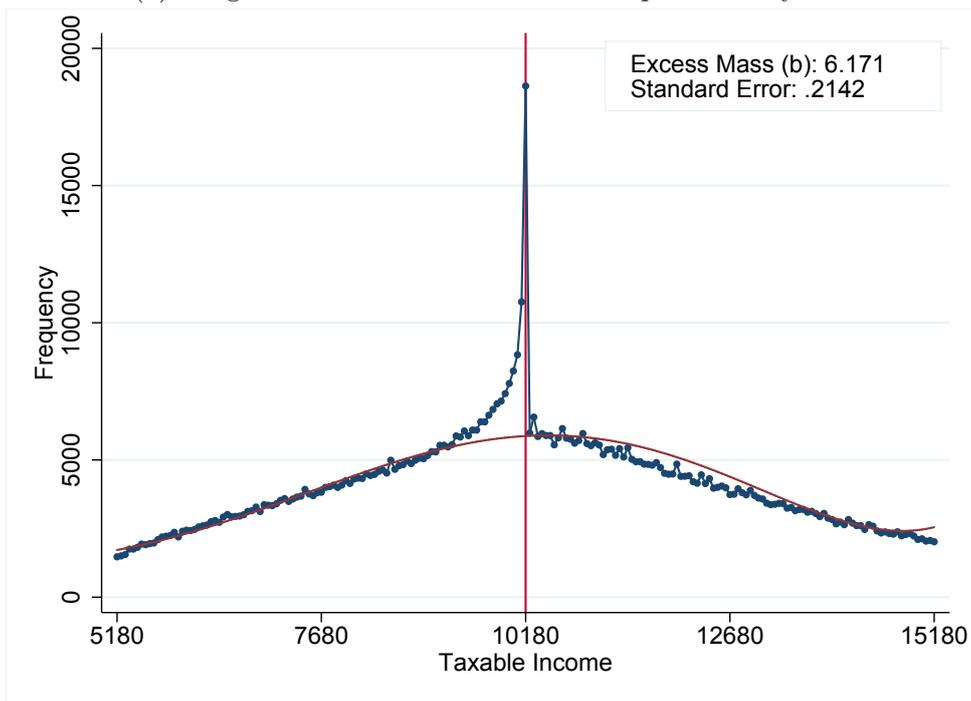


Figure 6: Bunching Estimates Taxable Income



(a) No gross income above first kink in previous 2 years



(b) At least one year of gross income above first kink in previous 2 years

Figure 7: Experience in paying taxes

Figure 8: Event Study Job Switchers

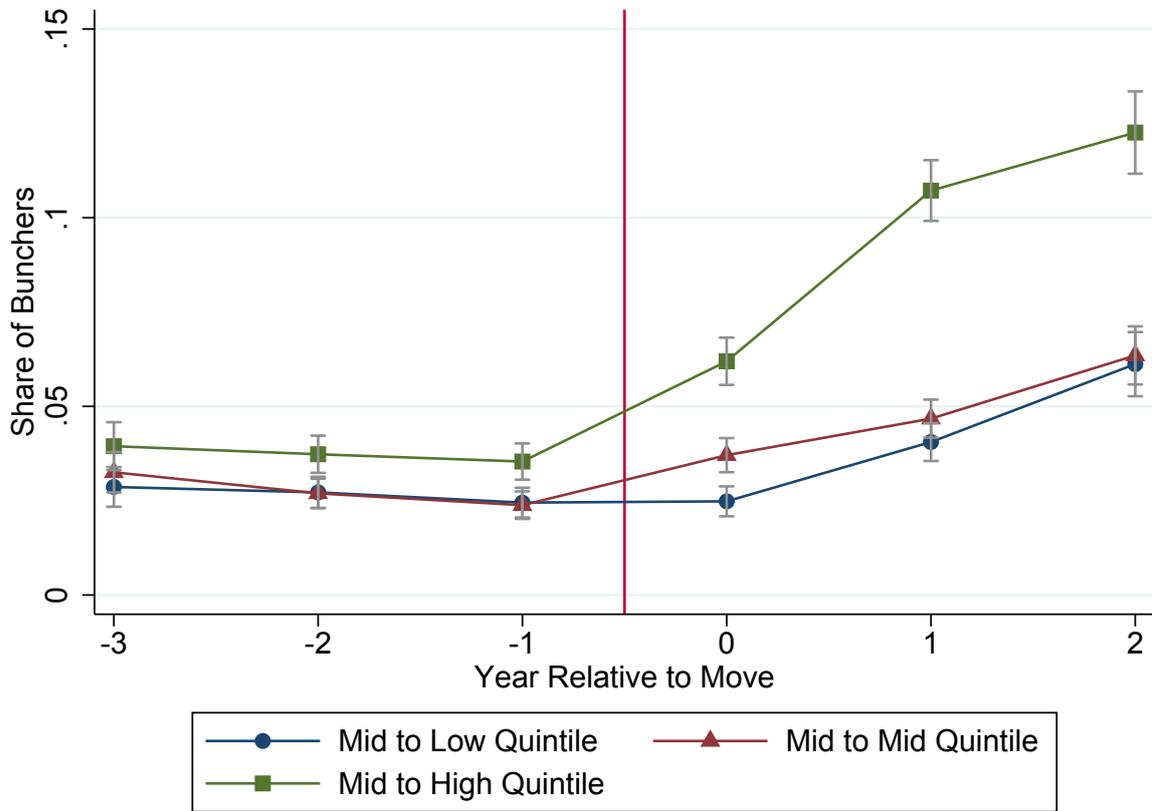


Figure 9: Coworker Learning - All

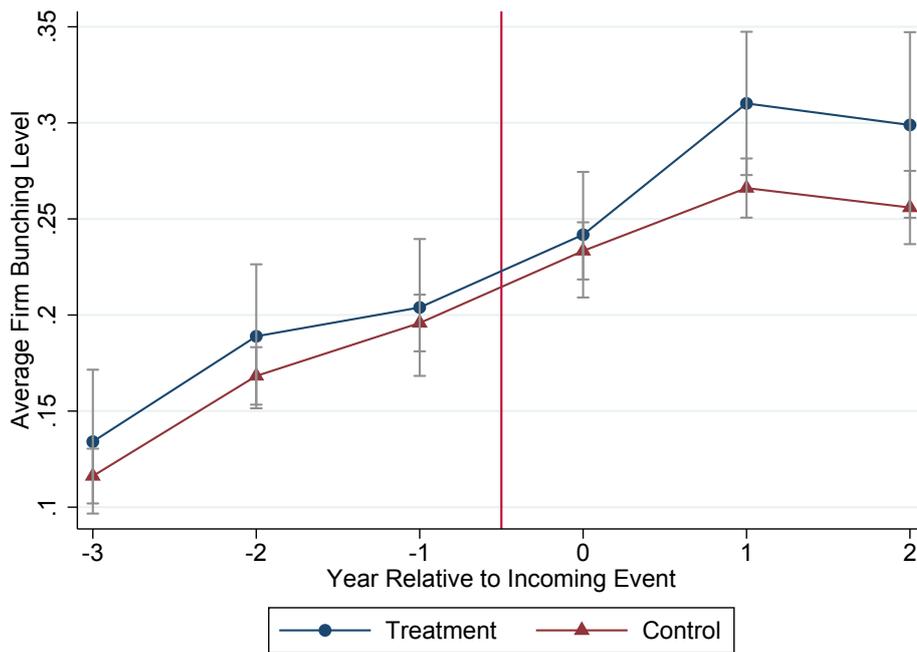


Figure 10: Coworker Learning - No Bunchers

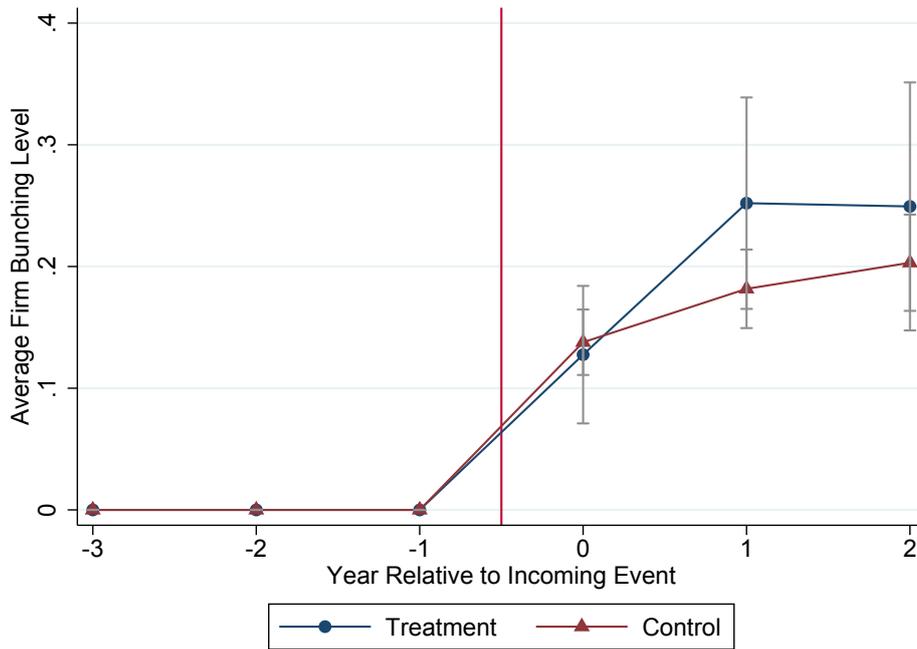
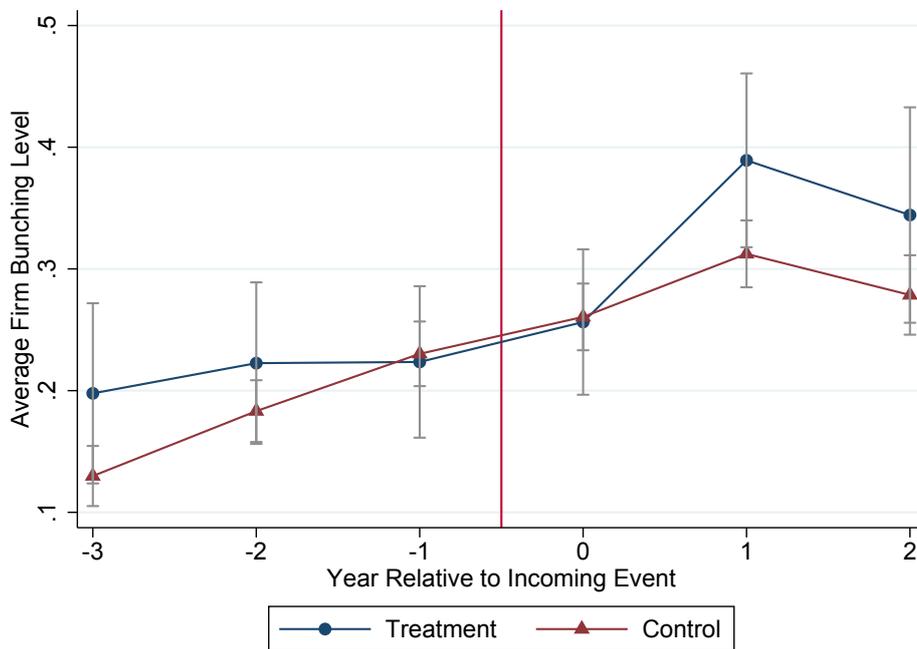


Figure 11: Coworker Learning - Small Firms



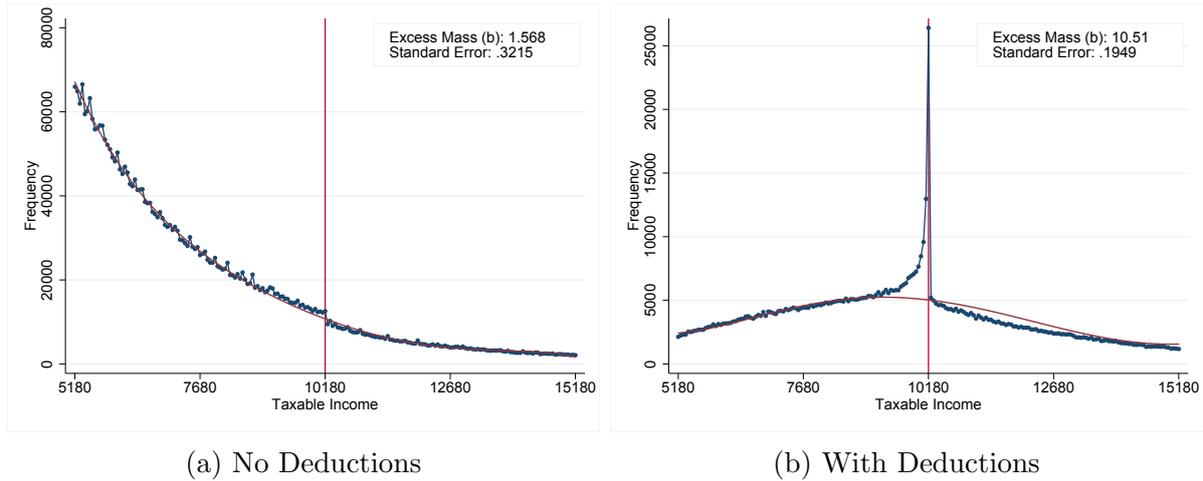


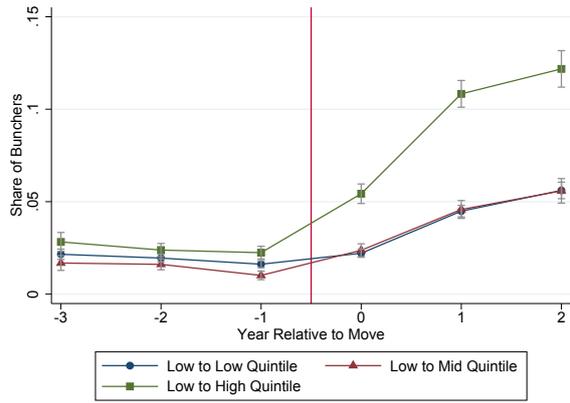
Figure A.1: The impact of filing deductions

## A Additional Figures and Tables

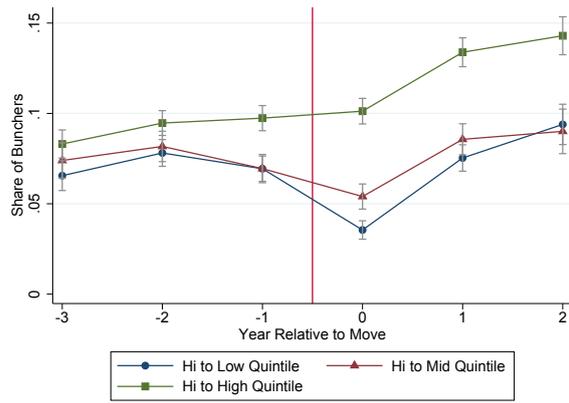
Further evidence for the fact that bunching is driven by reporting behavior can be found in Figure A.1. Individuals who do not file deductions for personal expenses do not display high levels of bunching (Figure A.1a). In contrast, individuals who file deductions (Figure A.1b) form a substantial excess mass to the left of the first kink in the tax schedule. The estimate here is extremely high (ten times as many individuals) and significant. Moreover, when only looking at gross income pooled in our sample period, our estimate of the bunching estimator is extremely small and insignificant (Figure A.5). Summing up, we find that in line with the large majority of research about behavioral responses to income taxation the reactions to tax incentives are mostly driven by reporting behavior rather than real labor supply responses. Furthermore, deductions for personal expenses are the primary tool used to avoid taxes.

The asymmetry of the response is further emphasized by the evidence in Figure A.2. The left panel shows bunching shares among workers who start from a firm in the lower quintile of the bunching distribution while the right panel refers to movers who start in the upper quintile. Among workers starting in the lower bunching quintile we see very similar patterns as before: individuals who move to the high quintile experience strong and sustained increases in bunching, whereas individuals moving to the low or mid quintile exhibit much smaller increases. Considering workers starting in the high

Figure A.2: Event Study Job Switchers



(a) from low bunching



(b) from high bunching

bunching quintile we see some small additional increases among those going back to the high quintile, whereas taxpayers moving to the mid or low quintile have a temporary decrease in their probability to adjust their taxable income.



		<b>DECLARACIÓN DE GASTOS PERSONALES A SER UTILIZADOS POR EL EMPLEADOR EN EL CASO DE INGRESOS EN RELACION DE DEPENDENCIA</b>			
EJERCICIO FISCAL	2 0 1 5	CIUDAD Y FECHA DE ENTREGA/RECEPCION	CIUDAD	AÑO	MES DIA
			QUITO		
<b>Información / Identificación del empleado contribuyente (a ser llenado por el empleado)</b>					
101	CEDULA O PASAPORTE	102	APELLIDOS Y NOMBRES COMPLETOS		
<b>INGRESOS GRAVADOS PROYECTADOS (sin decimotercera y decimocuarta remuneración) (ver Nota 1)</b>					
(+) TOTAL INGRESOS GRAVADOS CON ESTE EMPLEADOR (con el empleador que más ingresos perciba)	103	USD\$			
(+) TOTAL INGRESOS CON OTROS EMPLEADORES (en caso de haberlos)	104	USD\$			
<b>(=) TOTAL INGRESOS PROYECTADOS</b>	105	<b>USD\$</b>			
<b>GASTOS PROYECTADOS</b>					
(+) GASTOS DE VIVIENDA	106	USD\$			
(+) GASTOS DE EDUCACION	107	USD\$			
(+) GASTOS DE SALUD	108	USD\$			
(+) GASTOS DE VESTIMENTA	109	USD\$			
(+) GASTOS DE ALIMENTACION	110	USD\$			
<b>(=) TOTAL GASTOS PROYECTADOS</b>	(ver Nota 2) 111	<b>USD\$</b>			
<small>NOTAS:            1.- Cuando un contribuyente trabaje con DOS O MÁS empleadores, presentará este informe al empleador con el que perciba mayores ingresos, el que efectuará la retención considerando los ingresos gravados y deducciones (aportes personales al IESS) con todos los empleadores. Una copia certificada, con la respectiva firma y sello del empleador, será presentada a los demás empleadores para que se abstengan de efectuar retenciones sobre los pagos efectuados por concepto de remuneración del trabajo en relación de dependencia.            2. La deducción total por gastos personales no podrá superar el 50% del total de sus ingresos gravados (casillero 105), y en ningún caso será mayor al equivalente a 1.3 veces la fracción básica exenta de Impuesto a la Renta de personas naturales. A partir del año 2011 debe considerarse como cuantía máxima para cada tipo de gasto, el monto equivalente a la fracción básica exenta de Impuesto a la Renta en: vivienda 0.325 veces, educación 0.325 veces, alimentación 0.325 veces, vestimenta 0.325, salud 1.3 veces.</small>					
<b>Identificación del Agente de Retención (a ser llenado por el empleador)</b>					
112	RUC	113	RAZON SOCIAL, DENOMINACION O APELLIDOS Y NOMBRES COMPLETOS		
	1 7 6 0 0 1 3 2 1 0 0 0 1		<b>SERVICIO DE RENTAS INTERNAS</b>		
<b>Firmas</b>					
<b>EMPLEADOR / AGENTE DE RETENCION</b>			<b>EMPLEADO CONTRIBUYENTE</b>		
			FIRMA DEL SERVIDOR		

Figure A.4: Tax declaration form for filing deductions for personal expenses

Table A1: Job Switchers Potential Buncher

	Mid to Low		Mid to High	
	(1)	(2)	(3)	(4)
<b>Overall Effect</b>				
After event year	0.00360 (0.0200)	0.0130 (0.0221)	0.0622*** (0.0220)	0.0637*** (0.0229)
<b>Anticipatory Effects</b>				
Event year - 2	-0.0110 (0.0323)	-0.0338 (0.0336)	0.0543* (0.0293)	0.0404 (0.0310)
Event year - 1	-0.0280 (0.0351)	-0.0423 (0.0363)	0.0610* (0.0354)	0.0535 (0.0351)
<b>Post Treatment Effects</b>				
Event year	-0.0197 (0.0331)	-0.0283 (0.0349)	0.102*** (0.0329)	0.0993** (0.0388)
Event year + 1	-0.0198 (0.0408)	-0.0152 (0.0425)	0.106*** (0.0337)	0.100*** (0.0348)
Event year + 2	0.0242 (0.0497)	0.00290 (0.0508)	0.126*** (0.0445)	0.109** (0.0460)
Controls	No	Yes	No	Yes
Observations	5493	5493	5701	5701

This table reports results for a reduced version of the job-switcher sample from Table 5. The sample is restricted to individuals with gross earnings between 10180 and 20360 USD, that is individuals who can use their deductions to reduce their annual income below the threshold for paying taxes. We report results from the event study-type regressions. Due to the lower number of observations we use terciles instead of quintiles. The regressions are run for individuals starting in the mid-tercile of the bunching distribution and moving to the low or high tercile respectively. The outcome variable is an indicator for having taxable income in an interval of 1000\$ below the first kink. Standard errors (in parentheses) are clustered at the destination firm by year level. Significance levels are given by \* < 0.1, \*\* < 0.05, and \*\*\* < 0.01.

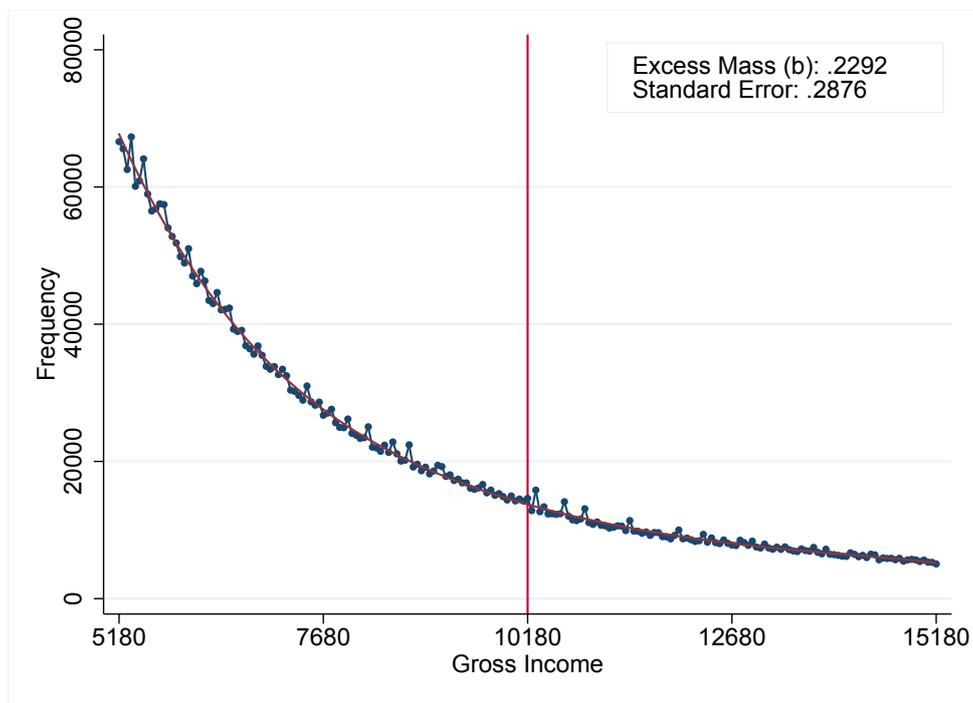


Figure A.5: Bunching Estimates Gross Income