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

– JOB MARKET PAPER –

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Abstract

We characterize the dynamics of behavioral responses to personal income taxes exploiting novel administrative data from Ecuador. The unique setting of a rapidly formalizing economy with increasing numbers of taxpayers and firms provides an ideal environment to study the role of information frictions. Our results show that with increasing experience in the formal sector, individuals are more likely to avoid paying taxes by reporting income below the exemption threshold ("bunching"). Exploiting variation in the knowledge environment induced by job switchers, we identify firms to be the drivers of individual learning processes. In particular, we are the first to show that individuals are more likely to bunch as their employer gains experience in the formal sector. We establish peers and experts as two important channels of information transmission between firms and quantify their importance through changes of a firm's coworker composition and accountant switches.

Keywords: Learning, Tax Avoidance, Information Frictions, Taxation and Development, Bunching, Behavioral Responses to Taxation

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1 Introduction

Formalization of developing economies is a key policy goal. Informal employment eluding government control represents a large portion of economies in low and middle income countries, estimated to be almost 50 percent in Latin America (ILO, 2014). While there is a growing literature looking into the determinants of formalization and its impact on key economic areas (Gerard and Gonzaga, 2016; Naritomi, 2016; Jensen, 2016; Pomeranz, 2015), little is known about the dynamic processes shaping the responses of economic agents that adjust to the formal system. In particular, it is unclear how individuals and firms new to the formal system learn about its incentives. Moreover, an emerging literature has highlighted the importance of behavioral aspects in shaping responses to tax incentives (Taubinsky and Rees-Jones, forthcoming; Benzarti, 2017). While a number of studies have explored general spillovers between taxpayers (Chetty, Friedman, and Saez, 2013; Paetzold and Winner, 2016), there is no clear consensus on how information frictions are overcome. This paper contributes to the literature by identifying specific channels of information transmission about tax adjustment opportunities.

We draw on novel administrative data on personal income tax (PIT) returns in Ecuador to assess how workers and firms learn about tax avoidance opportunities in a developing country. The environment of a rapidly formalizing economy with a steady inflow of new individuals to the tax system provides a unique setting to study dynamic information flows between taxpayers. We make three main contributions: First, we document individual dynamics in the usage of tax adjustment opportunities. With increasing tenure in the formal sector, individuals are more likely to avoid paying taxes. Exploiting variation in the information environment individuals face by analyzing a sample of job switchers, we provide evidence of the importance of the firm environment in explaining individual learning. Second, we analyze firm-level dynamics and document that as firms gain experience in the formal sector, their employees are more likely to bunch. Third, we contribute by identifying two specific channels of information transmission: peers (coworkers) and experts (accountants). Incoming coworkers have a lasting effect on the tax avoidance behavior of their new coworkers. Likewise, introducing a knowledgeable accountant into a firm increases the tax adjustment behavior of the firm's employees.

Tax avoidance in Ecuador is mostly driven by generous legal deduction opportunities for personal expenses in housing, health, nutrition, education, and clothing. These deduction possibilities are one of the main aspects of the government's policies to induce an increase in formalization. Adjustments in taxable income lead to a large and pronounced spike (bunching) in the distribution of taxable income just before the income tax exemption threshold. Using the established bunching estimator (Saez, 2010; Kleven, 2016), we quantify the excess mass and observe about four times as many taxpayers in the vicinity of the first kink of the marginal tax schedule as given by the counterfactual. There is no bunching in gross income, which we take as evidence for the fact that bunching is driven by reporting effects and not real labor supply responses. However, many individuals do not fully employ these deduction possibilities. Among those workers who could use the deductions to completely avoid paying taxes, 60 percent still pay some taxes (this share is decreasing over time and reaches just above 50 percent in 2015). 65 percent of those remaining taxpayers earn gross income in a range where they could even avoid paying taxes without actually having to hand in any receipts to the tax authority.[1] The low usage of easily accessible tax adjustment opportunities speaks to the presence of information frictions.

To document dynamic adjustments and learning processes, we begin by focusing on individual taxpayers' adaptation to the incentives of the formal sector. We estimate the prevalence of bunching among cohorts of taxpayers by their year of entry into the formal sector. We find clear evidence of individual-level learning: across all cohorts, bunching becomes stronger as individuals gain experience in the formal sector. We approximate the effect of experience through a quadratic polynomial and find strong initial increases in bunching activity which level off after about five years in the formal system. This finding leads to the conclusion that, with tenure in the formal sector, workers in Ecuador learn about the incentives and measures to avoid paying taxes. The correlation between experience in the system and bunching behavior remains strong and unchanged when

[1]Only if the value of deductions exceeds a certain reporting threshold are taxpayers obliged to hand in the receipts to the tax authority. More details in Section 2.

controlling for a range of observable characteristics including gross income, age, marital status and education.

However, it is unclear how exactly workers learn about the tax system. Exploiting the unique matched employer-employee component of our data and a research design based on changes in knowledge environments due to job transitions, we find asymmetric responses consistent with learning and memory. Individuals moving into a high bunching environment are more likely to bunch and individuals moving into a low bunching environment are just as likely to bunch as before. These findings confirm results in the literature (Chetty et al., 2013; Paetzold and Winner, 2016) and we take them as evidence that the firm environment is a crucial driver of individual learning on bunching opportunities.

This importance of the firm environment in shaping individual learning processes and their special role in submitting tax declarations motivates our interest in the firm-level dynamics of expanding the formal sector. We show that firms themselves are more likely to have bunchers among their employees as they gain experience in the formal economy. When looking at firm cohorts by their year of entry into the formal sector, we document a strong rise in the probability to have at least one buncher. However, conditional on a firm employing at least one buncher, the share of bunchers within the firm remains relatively stable over time. We conclude that for firms it seems to be the case that either information about bunching practices is available or it is not.

What are the determinants of a firm's information environment? We identify and quantify two specific information transmission mechanisms between firms: Peers and experts. To characterize the peers channel, we study coworkers coming into a firm and the knowledge they bring about bunching due to their tax avoidance behavior in their previous job. The experts channel is characterized by knowledgeable accountants who were previously working at or for a firm that was employing bunchers. We identify both of these effects through changes in the coworker composition and switches of accountants. Both the peers and experts channels are sizeable, leading to average increases in firm-level bunching activity by 21 and 13 percent respectively. We corroborate our findings in an alternative identification strategy based on event studies in subsamples with plausible control groups for both channels. Incumbent coworkers are significantly more likely to bunch among firms with new workers that were previously bunching than among firms with new workers that were previously not bunching. Likewise, firms with new accountants previously not at a firm with bunching activity are less likely to bunch than those with new accountants with bunching at their previous firm. However, when controlling for observable characteristics, this experts effect is not significant in this smaller sample.

Our findings are highly policy relevant since they give indications for tax authorities in designing audit strategies and deciding who should be targeted. Moreover, our results indicate that in settings where a policy instrument is only partially used by economic agents, this can have distributional implications. In our setting, the usage of the deduction opportunities is strongly related to specific demographic characteristics and certain types of firms. This increases inequality compared to a scenario with full adoption.

Literature Our paper contributes to the growing literature on bunching at kinks and notches in the tax schedule started by Saez (2010) and Chetty, Friedman, Olsen, and Pistaferri (2011). The method was refined and expanded to estimate further behavioral parameters influencing bunching behavior like frictions, fixed adjustment costs, and reference dependencies (Kleven and Waseem, 2013; Gelber, Jones, and Sacks, 2015; Seibold, 2017).[2] We provide novel evidence on the dynamics of bunching by following economic agents over time. We exploit changes in the bunching estimate in subgroups with different exposure to the formal system to quantify the learning process. Moreover, bunching in personal income taxes has been mostly found in developed countries and for subgroups with easy adjustment opportunities such as self-employed workers (Chetty et al., 2011; Bastani and Selin, 2014).[3] We look at bunching among wage earners in a development setting and find strong reactions to a very small kink.[4]

[2] For a comprehensive review, please refer to Kleven (2016).

[3] A notable exception is Kleven and Waseem (2013) who look at bunching of wage earners at notch points in Pakistan.

[4] 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.

This paper's main contribution is towards a small number of studies looking into knowledge diffusion and spillover effects in taxation (Chetty et al., 2013; Paetzold and Winner, 2016). These papers analyze the effects of moving into high or low information environments (regions and firms) and find similar effects as we do when analyzing job switchers. We extend this literature and identify and quantify two specific channels of information transmission: peers (coworkers) and experts (accountants).

Moreover, we contribute towards a growing literature on the determinants of formalization of developing economies (Gerard and Gonzaga, 2016; Naritomi, 2016; Pomeranz, 2015; Brockmeyer, Hernandez, Kettle, and Smith, 2016). We provide detailed evidence on the dynamics of individual and firm-level adjustments to the formal sector. Most importantly, we document the importance of experience and tenure in the formal economy for explaining the usage of tax avoidance opportunities.

More generally, our paper relates to the literature on taxation and development. The relevance of our study is underscored by recent work showing the rising importance of personal income taxes as countries develop (Besley and Persson, 2013; Jensen, 2016). A number of studies have shown in general how tax systems in low enforcement settings can differ to those in more developed economies (Gordon and Li, 2009; Best, Brockmeyer, Kleven, Spinnewijn, and Waseem, 2015; Keen and Slemrod, 2017). Corporate taxation and firm behavior in a development context (Asatryan and Peichl, 2017; Bachas and Soto, 2017) and in Ecuador in particular (Carrillo, Emran, and Rivadeneira, 2012; Carrillo, Pomeranz, and Singhal, 2017) have been studied extensively. The importance of the role of firms in driving tax avoidance and evasion opportunities has been put forward recently (Best, 2014; Kumler, Verhoogen, and Frias, 2015; Kleven, Kreiner, and Saez, 2016). We specifically investigate the dynamics and determinants of the information environment at the firm level.

A further contribution of our paper is to the literature on the role of accountants and tax preparers in facilitating tax avoidance behavior (Kopczuk and Pop-Eleches, 2007; Chetty and Saez, 2013; Mahon and Zwick, 2015). We provide evidence of the importance of a firm's accountant in driving tax avoidance behavior not of the firm itself but of its employees.

Finally, we contribute to the literature on the role of deduction opportunities in personal income taxation (Doerrenberg, Peichl, and Siegloch, 2017; Matikka, forthcoming). In line with these findings, our bunching responses are driven by reporting effects using deductions and not real labor supply responses.

The remainder of the paper is organized as follows. Section 2 provides information on the institutional background in Ecuador and describes the PIT system in detail. Section 3 gives detailed information on the various data sources employed in our study. In section 4 we present the results on the drivers of individual and firm dynamics. Section 5 concludes.

2 Institutional Background

Ecuador is a middle-income country with a large but shrinking informal sector.[5] In the past years the government has implemented a range of economic and political reforms aimed at expanding 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)[6], corporate taxes (22% of profits since 2013), a tax on foreign money transfers, and special consumption taxes. Figure 1a documents the strong growth of tax revenue in Ecuador in the past decade.[7] 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 as a

[5] According to a survey in 2006, about 70 percent of the labor force was employed in the informal sector (Canelas, 2015).

[6] Following a large destructive earth quake in 2016 the Ecuadorian government temporarily increased the VAT to 14 % until June 2017.

[7] The Ecuadorian economy was completely dollarized in 2000 following extreme hyperinflation.

result of the tax administration's wide-ranging efforts to increase tax compliance.

Importantly, the government has adopted a number of policies to increase formalization of the economy. The most relevant policy is the introduction of extensive deduction possibilities in income tax, substantially increasing 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 withholding 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.

Apart from a general hike in tax revenue, these formalization efforts induced a strong increase in the 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.

Personal Income Taxes (PIT) Ecuador has a unified PIT schedule which is levied on almost all regular sources of wage and self-employed income.[8] Tax liability in Ecuador is individually determined (no family taxation).[9] The PIT liability is calculated progressively with numerous small jumps in the marginal tax rate, starting at 5% and going up to 35%. Figure 2 gives an overview of the schedule of marginal tax rates in 2013. The cutoff income levels change yearly according to inflation,[10] the exact values since 2006 are displayed in Table 1. In 2008, the government enacted a series of tax system reforms, including increasing the top marginal tax rate from 25% to 35%.

PIT in Ecuador starts being levied only at relatively high levels. In 2013, the exemp-

[8]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.

[9]Additional to PIT, employees in the private sector pay 9.45% of their wage income in social security contributions and the employer pays 11.15%. Paying these social security contributions entitles people to a range of benefits including pensions, health insurance, disability insurance and unemployment benefits.

[10]The rate used for inflation adjustments ist 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.

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

The Ecuadorian tax system is unique in its generous deduction allowances for personal expenses in education, health, food, clothing and housing introduced in 2008 (Villacreses, 2014). The total deductible amount of personal expenses is limited to the smaller of 50% of individual income or 1.3 times the exemption threshold (in 2013 this was $1.3 \times 10{,}180 = 13{,}234$ USD). Each category is individually capped at 0.325 times the exemption threshold, except for health expenditures, which have an upper limit of 1.3 times the exemption threshold. To make receipts presentable to the tax authority, they must be issued to the name of the taxpayer or his/her dependents and include their unique identification number. Ecuadorian taxpayers are legally obliged to keep the receipts of all of their deductions. However, only if individuals claim deductions above a specific reporting threshold (50% of the tax free amount, or 5090 US$ in 2013)[11], must they submit the receipts of all of the claimed deductions to the tax authority via an online annex.

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 tax 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. While the ultimate responsibility for the overall correctness of these deductions

[11]Until 2010 this limit was set at $7500.

lies solely with the employee, this system induces a weak 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 et al., 2016).

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.[12]

3 Data and Descriptives

Our data combines several administrative datasets in Ecuador administered by the Ecuadorian tax authority *Servicio de Rentas Internas* (SRI). The core data consist of the universe of firm-reported personal income tax returns of regular employees (tax form F107) for the years 2006-2015.

We augment these tax records by three administrative datasets. First, we use unique individual identifiers to merge the data to the Ecuadorian civil registry (*Registro Civil*). This register data 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 registry in Ecuador (*Catastro de RUC*) based on unique firm identifiers. This registry contains firm-level data on industry affiliation, sector (public or private), time of formation of the firm, and place of registry. Lastly, for the subset of corporate firms we draw on their corporate tax declarations to identify the accountant working at the firm.[13] We end up with detailed matched employer-employee data that allows us to track taxpayers, firms, and coworkers over time.

[12] 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.

[13] Firms are obliged to file a corporate tax declarations if they have annual turnover above $60000. Firms can have several corporate tax declarations and accountants per year. Here we take all accountants given in any of a firm's corporate tax declarations as being at the firm in a given year. Likewise, some accountants work for several firms in a given year. This is exactly the source of variation we are exploiting in Section 4.2.2.

Importantly, in Ecuador personal income tax returns are third-party reported by the employer and include information on the level of deductions. A significant fraction of wage earners has various employers throughout a given calender year and therefore multiple tax declarations. We sum up the different income values to compute a unified measure of individual yearly income. Moreover, we consider the spell with the highest earnings as the main employer. We deflate all earnings to real 2013 USD values using the same consumer price index that is employed by the SRI to adjust the tax brackets annually (see footnote 10). Thereby the tax brackets, even though they change yearly in nominal values, remain unchanged in real terms.

Throughout our analysis, we exclude all individuals employed in the public sector and only focus on private sector employees for three main reasons. First, public sector employees face different incentives than private sector employees, and their pay is often regulated by predetermined government pay scales. Second, the main drive in formalization of the past years was being carried out in the private sector as the public sector was already formal by definition. Third, private sector employees might have better opportunities to adjust their taxable income by bargaining with their employer about wages, and employers in the private sector might provide more support in filing the deductions.

Figure 3 displays the reported 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 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.

The distribution of *taxable* income in Figure 4, however, looks very different. Taxable income is gross income minus any deductions. There is a clear and very pronounced spike in the distribution just before the exemption threshold at 10,180 USD.[14] While taxpayers make strong adjustments to their taxable income, there are no visible adjustments to their gross income. We take this as evidence for the observations that bunching is driven by reporting effects and not real labor supply responses.

While bunching is strong and pronounced at the exemption threshold, we do not observe any bunching at subsequent kink points of the marginal tax schedule. We have a number of explanations for this phenomenon. The exemption threshold, even though it is associated with a very modest increase in the marginal tax rate of only 5%, is arguably the most salient aspect of the tax schedule. Behavioral biases may make the disutility associated with the first dollar of tax payments discretely higher than any other subsequent increases in the tax liability. Moreover, individuals may perceive a discontinuity in audit probabilities at the exemption threshold and prefer to stay under the radar of the tax authority. Lastly, the marginal returns to filing more deductions vanish once taxpayers have successfully reduced their taxable income below the exemption threshold. Throughout the rest of this paper, we exclusively focus on explaining the dynamics of bunching at this exemption threshold.

The relevance of dynamic aspects in driving tax adjustment behavior becomes especially pronounced when tracking the number of taxpayers over time. Figure 5 documents a strong 2.5-fold increase in the number of high-wage earning private sector employees with tax-liable gross income.[15] At the same time, the usage of the generous deduction possibilities increases disproportionately stronger after their introduction in 2008. Figure 5 depicts a clear wedge between the number of individuals with *gross* income above the exemption threshold and those with *taxable* income above the exemption threshold. The gap between these two lines is introduced with the deduction possibilities in 2008 and strongly increases over time. This increase in the absolute and relative difference between the number of taxpayers with tax liable gross income and those actually paying taxes reflects a growing usage of tax avoidance opportunities over time. The main part of

[14] We would like to underscore that this is pooled data in real 2013 US$ values. In nominal terms, taxpayers re-adjust their taxable income to the yearly changing exemption threshold.

[15] The increase in the overall number of private sector employees is proportional but about an order of magnitude larger: The number increases from about 1 million to 2.5 million.

our analysis quantifies the bunching underlying this behavior and examines the learning processes driving the dynamic increases in the usage of these tax avoidance opportunities.

4 Results

In this section we present empirical results from our analysis of learning dynamics about avoidance opportunities in personal income taxes. We start by using the bunching methodology developed by Saez (2010) and Chetty et al. (2011) to estimate the extent of behavioral responses to taxation and document general learning dynamics. The first part of this section explores the dynamics of individual learning and exploits a sample of job switchers to identify firms as the driving environment for individual learning. The second part of the section documents firm-level dynamics in tax adjustment behavior and identifies peers and experts as the main drivers of information transmission on bunching opportunities.

To quantify the amount of bunching at the exemption threshold, 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 its absence. The difference between the observed density and the counterfactual is used to compute the excess mass as multiples of the counterfactual.[16] Figure 6 displays the distribution of taxable income around the kink. The empirical density is represented by the blue dots 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 four times as many individuals are located around the kink compared to the expected mass under the counterfactual of no kink.[17]

Table 2 displays the estimated excess mass separately for each year in the sample

[16]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.

[17]When using these estimates to calculate elasticities we find extremely large values. However, we do not believe these to be very informative about the underlying labor supply elasticity or elasticity of taxable income for a variety of reasons. First, as discussed in Section 3, there are number of factors exacerbating bunching at this first kink. Second, recent research has shown that in the presence of deduction possibilities it becomes difficult to structurally interpret inferred elasticities (Doerrenberg et al., 2017).

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. This corresponds to a general increase in bunching activity driven by an expansion in the use of the deduction possibilities. Moreover, this table presents evidence for an interesting substitution mechanism between different forms of tax avoidance. In 2006 and 2007, before the introduction of the deduction possibilities, we find bunching activity in *gross* income (identical to that in taxable income). Starting in 2008, there is a clear shift away from bunching in gross income and towards bunching in taxable income. We can rationalize this with the observation that bunching in gross income is relatively more costly than bunching in taxable income.

4.1 Individual Dynamics

In this section we explore individual dynamics in the usage of tax adjustment opportunities. First, we document strong increases in bunching as individuals gain experience in the formal sector. Second, we exploit an identification strategy based on job switchers to assess the effects of the firm environment in driving individual learning processes.

4.1.1 Individual Learning

We assess whether the overall increase in bunching and tax avoidance activity is driven by individual experience in filing taxes and working in the formal sector. To this end, we exploit the massive expansion in the number of taxpayers in Ecuador and construct cohorts of individuals by their year of entry into the formal sector. This research design allows us to compare bunching levels of the same set of individuals depending on their tenure in the formal system. To hold the sample composition constant within cohorts, we only consider individuals we observe without interruption once they entered the formal economy.

Table 3 displays bunching estimates over time for our cohort analysis. Each row corresponds to one of the cohorts that entered the formal sector between 2007 and 2014. The columns indicate how the level of bunching changes over time for these cohorts. For each cohort, there is a clear increase in the amount of bunching in taxable income as experience in the formal sector increases. Moreover, the estimates become more precise over time, indicating less heterogeneity within cohorts over years. Individuals entering the formal economy in 2010 for instance had a modest (and insignificant) excess mass of 0.62 in their first year which increased to 5.56 in 2015. We observe this steep increase throughout all cohorts.[18] Learning did not only occur within cohorts but also across cohorts as individuals entering the formal economy in later years tend to start at higher degrees of bunching.[19] Bunching in gross income, however, stays relatively low and does not seem to increase as individuals gain experience in the formal system.

This learning process can be described well by a quadratic polynomial in years of experience. We find strong initial increases in bunching activity: Between the first and the second year in the formal sector, experience leads to an increase in the bunching mass of 0.6, corresponding to a sizeable increase in the implied elasticity of taxable income from 0.25 to 0.31. This effect decreases over time and levels off completely after five years of experience.[20]

One major concern in comparing bunching estimates according to tenure and experience in the formal system is that factors like wage growth and selection on (un)observables may confound our results. These factors are already mitigated to a large extent by the fact that the bunching estimator is a local estimator measuring the excess mass for a given subsample and in the vicinity of the kink. Moreover, by holding constant the individuals within a cohort, we abstract from a range of selection effects.

To address any remaining selection issues, we construct a time-varying individual mea-

[18]One issue with this analysis might be that in the first year of working in the formal sector, individuals did not work during the full year or were otherwise hindered in their ability to use tax adjustment opportunities fully. Throughout all cohorts, however, bunching also increases substantially during the subsequent years of an individual's time in the formal sector.

[19]Notable exceptions to this are the 2007 and 2008 cohorts, which start at relatively high levels. The 2007 cohort has the same amount of (not very significant) bunching in *gross* income levels in 2007, indicating other mechanisms at work than the tax avoidance mechanisms studied in this paper. The 2008 cohort might be inherently different to the other cohorts as these are the very first individuals affected by the government's drive to formalize the economy.

[20]We approximate this quadratic effect through an OLS regression of the bunching estimate on experience (measured as years in formal sector) and experience squared. We include time fixed effects to account for a general increase in bunching activity over time. As this regression draws on estimates of varying sample size it is difficult to interpret the standard errors.

sure of experience with the tax system and look at the correlation between this measure and the probability of bunching.[21] Importantly, we hold constant relevant factors such as income levels and socio-demographics like age, gender, marital status and education. Table 4 presents results from simple probit regressions with an indicator for bunching as the outcome variable. We define bunching as having taxable income within the range of 1000$ to the left of the exemption threshold and restrict the sample to individuals in the years 2008-2015 with gross income above the exemption threshold but still within the relevant range for bunching using the deduction possibilities. Column (1) of Table 4 shows that having earned high income above the exemption threshold in the past 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 this experience effect remains comparable. The regression furthermore provides insight into which demographic characteristics are important in determining individual bunching behavior. 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 subsection strongly supports the hypothesis of individual learning dynamics in tax bunching. We provide robust evidence of individuals increasing their bunching activity as they gain experience in the formal sector. The next subsection turns to the question of how learning takes place and investigates how individuals react to changes in their information environment.

4.1.2 Job Switchers

The strong increase in bunching activity documented in the previous section supports the hypothesis that learning and information availability are important aspects of individual tax filing behavior. This section explores these learning dynamics in more detail and establishes the importance of the firm environment in driving individual learning

[21]This experience measure keeps track of whether individuals have had gross earnings above the exemption threshold during the previous two years. Individuals with lower income have no tax liability and no incentive to learn about the deduction possibilities. In Figure A.6 in the appendix, we report higher bunching estimates for individuals with experience than for those without.

processes.

To gain insights into the impacts of the firm environment on tax avoidance behavior, we draw on a sample of job switchers and exploit variation in the information environment individuals face. Following Chetty et al. (2013), we compare tax avoidance behavior of workers moving into a high-bunching environment to those moving into a low-bunching environment. To this end, we draw on the universe of formal sector job transitions in Ecuador. To keep sample composition fixed across years, we only consider job transitions where we observe at least two consecutive years before and after the job switch. Moreover, we only consider job switches of the main employer[22] and only an individual's first job transition[23]. Hence, we end up with a sample of 152,617 job transitions that occurred between 2010 and 2014.

We characterize the job switchers' information environments by assigning their origin and destination firms to quintiles based on the share of coworkers who are bunching.[24] Table 5 reports summary statistics for our sample of job switchers. The demographic characteristics are relatively balanced between the full sample in column (1) and switchers into the mid, low or high quintile in columns (2)-(4). Moreover, in the two years before the switch earnings and average usage of tax adjustment opportunities are relatively comparable between destination quintiles, with slightly higher values for individuals moving into the high quintile. In the two years after the switch there are, however, sizeable differences depending on the destination quintile. We will explicitly address these and further selection issues in the event study designs below.

Using an event study graph, we observe the dynamic adjustment process of individuals depending on the quintile they are moving towards. Figure 7 plots the share of bunchers[25] among workers starting from a firm in the mid-quintile of the bunching distribution. The

[22]The main employer is the one with the highest annual earnings. Job switches are by definition to a firm the individual has not worked at before.

[23]In robustness checks we consider the subsample of individuals who switched jobs only once with no change in the results.

[24]For every year, we compute the distribution of the share of coworkers who bunch and split the sample into quintiles. As before, we define bunching as reporting taxable income of 1000US$ to the left of the exemption threshold. To abstract from individuals too far away from the exemption threshold, we draw on the full sample of private sector employees with gross earnings between 5000 and 25000 USD.

[25]Defined as those who report taxable income in a $1000 window to the left of the exemption threshold.

horizontal axis indicates the year relative to the move with year zero being the first year at the destination firm. The data show a clear asymmetric pattern of adjustment. The share of bunchers among workers switching to a high-bunching firm sharply increases after the transition, resulting in the bunching share more than doubling its pre-switch level after three years. In contrast, even though we observe a moderate overall upward trend, bunching probabilities remain relatively unchanged for job transitions into a mid- or low-bunching environment.[26]

Figure 7 indicates parallel and stable pre-switch trends between individuals moving to firms in different parts of the bunching share distribution. While this lends credibility to standard parallel trends assumptions, the descriptive analysis has shown selection in terms of income between these groups of taxpayers. To address these issues, we employ three differing regression based event study research designs controlling for unobserved heterogeneity and a range of observed characteristics such as earnings before and after the job switch.

Our identification strategy is based on using individuals switching from a firm in the mid quintile to a different firm in the same quintile as a comparison group. We compare their bunching behavior to that of individuals switching from the mid to the high quintile. Among the subsample of individuals starting in the mid quintile and switching either to the mid or high quintile, we estimate

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

The dependent variable Y_{it} measures bunching activity as an indicator for individual i having taxable income within a \$1000 window to the left of the exemption threshold at time t. The indicator variable $post_{it}$ takes on the value of one in the years after the job switch and $quintile_i$ indicates if an individual moved to the high quintile. Accordingly, δ is our main coefficient of interest measuring the overall effect of moving to a high or low

[26] 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 transitioning to the top quintile than among those moving to the mid or low quintile.

bunching firm. We account for various sources of unobserved heterogeneity by including individual fixed effects (α_i), time fixed effects (λ_t) and fixed effects in event time (γ_k). Last, we control for time-varying individual and firm characteristics X_{it} including gross earnings, age squared, firmsize, industry classification and corporate firm status.[27] We run a parallel analysis for individuals switching from a firm in the mid to the low quintile with $quintile_i$ being an indicator for the low quintile.

The estimates are displayed in Panel A of Table 6. Columns (1) and (3) are without and columns (2) and (4) with the controls X_{it}. The results confirm the importance of the firm environment in driving 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.

In a second related event study design, we explicitly look at the timing of the effects. Particularly, we modify the regression equation

$$Y_{it} = \beta_0 + \sum_{k=-2}^{k=2} \delta_k D_{it}^k \times quintile_i + \theta X_{it} + \alpha_i + \lambda_t + \sum_{k=-2}^{k=2} \gamma_k D_{it}^k + \epsilon_{it} \tag{2}$$

to include the coefficients δ_k measuring the anticipatory and post treatment effects reported in Panel B of Table 6. We find no evidence of anticipatory effects before any job switch. Switching into a high quintile firm leads to a persistent increase in bunching strongest in the second year after the move. In contrast, switches to a low bunching environment are not associated with any effects.

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 separate comparison group anymore. Specifically, we estimate

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

[27] In various sensitivity checks, 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. We furthermore estimate the same regression without the fixed effects in event time D_{it}^k and find no substantial change in the direction of the results.

with the variables as defined above.[28] Our coefficients of interest γ_k are reported in Panel C of Table 6. We find very similar results to before and take this as further evidence for the robustness of our findings.[29]

This subsection provides evidence for asymmetric adjustment patterns consistent with learning and memory as have been found among self-employed in the US (Chetty et al., 2013) and commuters in Austria (Paetzold and Winner, 2016). We conclude with the observation that the firm environment is crucial in driving individual learning on bunching opportunities. In the following sections, we characterize firm-level knowledge about tax adjustment opportunities and analyze the channels through which information is spread among firms.

4.2 Firm Dynamics

The previous section has documented the importance of the firm environment in shaping individual learning processes. The institutional setting in which firms directly submit tax declarations with the value of deductions on behalf of their employees further motivates the study of firms. This section analyzes firm-level dynamics and documents a strong increase in the likelihood to have bunchers in the workforce as the firm gains experience in the formal sector. Moreover, we identify two key mechanisms of information transmission between firms: peers and experts.

4.2.1 Cohort Analysis

This subsection analyzes bunching behavior through the lens of the firm by focusing on firms' experience in the formal sector. We document a strong increase in the availability of information on bunching opportunities at the firm level.

We measure firm-level information on tax adjustment opportunities by looking at the

[28] In order to rule out any compositional effects, we furthermore restrict the sample in this regression to only include observations from the two years before and after the move for which we have a perfectly balanced panel.

[29] In order to lend credibility to these results we present the same set of regressions in Table A1 in the appendix restricting the sample to individuals with gross income in a range where bunching at the exemption threshold is possible. Even though the sample is smaller, we find no changes in the results. If anything, the magnitude of the effects is larger.

number of employees bunching at a given firm. To do so, we define *potential bunchers* as individuals with gross earnings in a range allowing them to lower their taxable income below the exemption threshold by using deductions. In 2013 real USD, this is gross earnings between 10180 and 20360 USD. Analogously to the individual level cohort analysis in section 4.1, we follow cohorts of firms after they first appeared in the formal sector.[30] Table 7 reports the firm-level probability to bunch, that is the share of firms with at least one buncher. Evidently, there is a strong increase in the share of firms that employ bunchers over time for each of the cohorts. Moreover, new cohorts start at higher bunching levels than previous cohorts. Lastly, within a given year, firms which entered the formal sector earlier exhibit higher bunching levels. We interpret this as evidence that the increase in bunching activity at the firm level is driven by experience and knowledge acquired in the formal sector and is not just a result of the general increase in bunching activity over time.

Table 8 focuses on the share of bunchers within a firm *conditional* on the firm having at least one buncher. This share is calculated as the number of bunchers relative to the number of potential bunchers.[31] As before, we group these firms by cohorts of entry into the formal sector. In general, the share of bunchers conditional on any bunching at the firm is relatively modest. This can be explained by the fact that potential bunchers in the higher part of the income distribution would need to claim deductions almost at maximum levels (here half of their income) in order to avoid tax payments.[32] Over time, however, this share does not increase notably. Moreover, there seems to be little dispersion in the share within a given year.

In summary, the increase in overall bunching levels is primarily driven by new firms entering the set of bunching firms. Experience of the firm in the formal sector leads to a higher probability to engage in bunching at the firm level.[33] Given that a firm has

[30]We restrict our sample to firms that employed potential bunchers throughout all years since their first appearance in the formal sector.

[31]We restrict the analysis to firms with at least five potential bunchers such that the share is not driven by a large number of firms with very few potential bunchers.

[32]In fact, within a given firm, individuals who are not bunching but could be bunching have significantly higher income than those that are bunching.

[33]In a robustness analysis, we looked at an indicator for being a potential buncher and avoiding taxes (having taxable income anywhere below the exemption threshold) instead of bunching (having taxable

taken the decision to allow for bunching, at least on average a relatively stable fraction of workers (around 30 percent) makes use of these bunching opportunities. In order to gain a more detailed understanding into what drives these firm-level decisions to start bunching, the following section analyzes the channels of information transmission between firms.

4.2.2 Channels of Information Transmission

In the previous sections we have seen that firms represent the relevant information environment driving individual learning about tax adjustment opportunities. Moreover, firms themselves seem to acquire information on bunching opportunities as they gain experience in the formal sector. In this section we analyze the determinants of the firm information environment and focus on two important information transmission mechanisms we are able to identify in the data: Peers and experts. The peers channel, specifically coworkers and their experience with bunching, represents an important aspect of the information environment at a given firm. We hypothesize that coworkers with previous experience in bunching might induce their colleagues to engage in bunching themselves. Our second channel focuses on accountants as firms' experts on taxation. Here we hypothesize that accountants previously working for a firm with bunching activity might bring knowledge about bunching opportunities to their new firm. We identify the effect of these two channels through changes in the coworker environment and accountant switches.

In line with our previous results highlighting the importance of the firm-level probability to bunch, we seek to identify the drivers of whether firms' employees bunch or not. To abstract from compositional effects and only look at firms with employees for whom bunching is possible in all periods (potential bunchers), we draw on the same panel of firms used in the cohort analysis in Section 4.2. However, we restrict ourselves to the subsample for which we have data on the corporate income tax declarations and thereby an identifier for the accountant. We measure the effect of both of our information transmission channels by estimating

income in a 1000US$ window below the threshold). Even though overall bunching probabilities and shares of bunchers are higher, the general conclusions of this section remain unchanged.

$$Y_{jt} = \beta_0 + \beta_1 coworker\_bunch_{jt} + \beta_2 accountant\_bunch_{jt} + X_{jt} + \alpha_j + \lambda_t + \epsilon_{jt} \quad (4)$$

The outcome variable Y_{jt} is an indicator for firm j capturing whether one or more of its employees is bunching at time t. The main variables of interest are $coworker\_bunch_{jt}$ and $accountant\_bunch_{jt}$. The first variable $coworker\_bunch_{jt}$ is a measure of a firm's peer knowledge environment. In particular, it is an indicator for a firm having an employee who was bunching at the previous employer.[34] The second main explanatory variable $accountant\_bunch_{jt}$ measures information flows about tax adjustment opportunities stemming from a firm's expert on tax-related matters. We are interested in accountants bringing external knowledge on bunching into a given firm. The indicator $accountant\_bunch_{jt}$ takes on the value of one whenever a firm's accountant was working for a different firm with bunching activity in the periods prior to the current one.[35]

Throughout these regressions, we include firm (α_i) and time (λ_t) fixed effects and therefore control for unobserved firm heterogeneity and general time effects. Due to the inclusion of these fixed effects, the variation that is driving the results comes from *changes* in the peer composition and *switches* in the accountants of a given firm. To account for any remaining confounders, we control for a range of time-varying firm level controls X_{it}. These include demographic employee characteristics like average age, share of married employees, share of female workers and share of workers with tertiary education. We also control for average income levels at a firm, indicators for fixed groups of firm size, industry and region (province) indicators, and an indicator for whether a given firm has employed bunchers in previous years.

Table 9 reports the results on the effects of these information transmission channels. Columns (1) and (2) quantify the channel of information transmission through peers.

[34] We only consider incoming coworkers who were bunching in the year before joining their current firm and had gross income in the range for potential bunchers. Moreover, the $coworker\_bunch_{jt}$ indicator is equal to one in all periods in which this incoming buncher remains at the destination firm.

[35] Note that, as explained in Section 3, accountants can work for several firms at the same time. In this case even a single accountant at a given firm can differ over time in term of his knowledge about bunching.

Having an incoming employee who was bunching previously is associated to an increase in the probability that any of a firm's employees bunch by 11 percentage points, or 9.1 percentage points after including control variables. With on average 42.9 percent of the firms in this sample employing bunchers, this is a strong effect corresponding to an increase in bunching activity by about 21 percent. Likewise, periods in which a firm has a knowledgeable accountant are associated with increases in bunching of 5.5 percentage points when including controls, which corresponds to an increase in firm-level bunching by about 13 percent. The fact that these effects remain relatively unchanged when including both of them simultaneously in columns (5) and (6) supports to the hypothesis that these are two separate mechanisms.

Table 10 shows results from a similar regression using the subset of firms with at least one buncher. As outcome variable we now use the share of bunchers among potential bunchers. This outcome is thereby conditional on bunching already happening at the firm and is our previously introduced measure of the firm-level intensive margin bunching decision. Both the coefficients on the peer information channel (incoming buncher) and the experts channel (knowledgeable accountants) are very small and insignificant when including controls. We take this as evidence that neither peers nor experts have an effect on the intensive margin bunching level conditional on a firm already employing bunchers. This is in line with our results in Section 4.2.1 showing that the strong overall increases in bunching can be attributed to firms joining the group of bunching firms and not to an increase in the intensity of bunching at firms already employing some bunchers.

In order to get a grasp of what types of firms help their employees bunch, we can draw on our rich firm-registry data to characterize bunching firms according to observables. For this analysis we use the full set of firms which are employing potential bunchers in any given year.[36] Table 11 reports the results from a simple OLS estimation regressing our previous indicator for having any bunchers on a set of observable characteristics as well as year fixed effects. Firms with younger and more female workers are more likely to engage in bunching. Larger firms' employees are also more likely to bunch. Industry

[36]The results look very similar for the subset of firms that fulfill the specific criteria necessary for the previous regressions on the channels of information transmission.

affiliation seems to play an important role in determining a firm's bunching activity. It is remarkable that the strongest positive coefficient belongs to firms in the financial sector, as we expect their employees to be most knowledgeable about tax adjustment opportunities.

To summarize, we have shown the importance of two key mechanisms in transmitting information about tax adjustment opportunities: peers (coworkers) and experts (accountants). Both play a crucial role in transmitting information between firms and are a key factor in explaining the rise in firm-level extensive margin bunching shares. The next section specifically focuses on the peers channel and quantifies the impact of incoming bunchers on their coworkers' tax adjustment activity.

Peers This section focuses specifically on the peers channel and analyzes and quantifies how incoming coworkers affect the behavior at their new firm. We find strong spillover effects of new coworkers on the probability that incumbent coworkers will bunch.

We quantify this peer 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 due to their gross income in the year before joining the new firm as in the beginning of this Section. We only consider firms hiring new workers once in the years 2010-2014 and in which we can observe at least two years before and two years after the event. These restrictions provide a sample balanced in event time and allow us to abstract from various treatments happening sequentially.

Among the firms with incoming potential bunchers, we divide the new employees into those that reduced their taxable income to just below the exemption threshold ("bunchers")[37] 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 12 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

[37] We again take at an interval of 1000 USD to the left of the first kink.

between the two groups (58 and 61 employees) is comparable. There are some differences in terms of wages and tax-filing behavior in the year before the arrival of new co-workers. We control for these and further unobserved heterogeneity in our identification strategy detailed below.

Using a similar event study methodology as in Section 4.1.2, we plot the share of firms with bunchers among their incumbent workers in both treatment and control group relative to the year of hiring the new coworker. By focusing only on the incumbent workers, we effectively calculate the "leave-out" version of our previous firm-level probability to bunch. This indicator disregards the incoming coworker and focuses only on the employees already working at a given firm. The results in Figure 8 suggest that incoming workers have a strong effect on the tax adjustment behavior of their coworkers. Firms in the treatment group are much more likely to have bunchers among their incumbent employees after receiving a new coworker.

Table 13 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 4.1.2. Specifically, we estimate

$$Y_{jt} = \beta_0 + \delta post_{jt} \times treat_j + \theta X_{ij} + \alpha_j + \lambda_t + \sum_{k=-2}^{k=2} \gamma_k D_{jt}^k + \epsilon_{jt}. \tag{5}$$

where Y_{jt} is an indicator for whether the incumbent workers bunch, $post_{jt}$ is an indicator for observations after the new co-worker joined the firm, $treat_j$ is an indicator for a firm receiving an incoming buncher. We include fixed effects at the firm (α_j), time (λ_t) and event-time (D_{jt}^k) level and in X_{jt} we control for firmsize 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:

$$Y_{jt} = \beta_0 + \sum_{k=-2}^{k=2} \delta_k D_{jt}^k \times treat_j + \theta X_{jt} + \alpha_j + \lambda_t + \sum_{k=-2}^{k=2} \gamma_k D_{jt}^k + \epsilon_{jt}. \tag{6}$$

In this regression the coefficients δ_k measure the anticipatory and post treatment effects. These coefficients, along with the estimate for the overall effect from equation (5), are reported in Table 13. Even when controlling for unobserved heterogeneity and our observables, the peer learning channel is strong and pronounced. An incoming buncher increases the probability that at least one of the incumbent coworkers bunches by about 5 percent. The effects are strongest in the second year after the incoming event, consistent with the idea that it takes some time for incoming coworkers to spread the information to the new firm environment.[38] In the appendix we conduct a heterogeneity analysis by firm size. Figures A.7a, A.7b and A.7c depict the same event study for small, medium and large firms respectively. As expected, we find the effect of coworkers on their peers to be largest for small firms and to become smaller the larger the firms are.

Experts We now focus our attention on the accountant channel. In a similar event study design exploiting variation in the knowledge of accountants we find clear evidence for the effect of accountants on firm-level bunching behavior. However, due to sample restrictions, some of these effects do not hold through when including the full set of controls.

The main idea behind quantifying the expert information transmission channel is to assess whether firm-level bunching behavior changes after firms receive new accountants.[39] A new accountant changes the information environment at a firm. Using an event study design we analyze the experts channel by comparing specific treatment and control groups. The firms in the treatment group receive a knowledgeable accountant who was previously working at a firm with bunchers. The control group also receives a new accountant, but this new accountant was previously working for firms without bunchers even though those firms had employees with gross income in the relevant range for bunching (potential bunchers).

We examine the universe of accountant switches observed in the corporate tax decla-

[38] In unreported results we additionally identify the peer channel within the sample of treated firms purely through the timing of the effect akin to the regression strategy in equation (3) and find very similar results.

[39] Some firms have various accountants and many accountants work for several firms.

rations. As outcome variable we take the share of firms with bunchers in a given year. We calculate this indicator for all firm-year observations in which a firm is employing potential bunchers. Much like in our previous event study analyses, we make a number of restrictions to guarantee tractability and credibility of the results. We exclude cases were firms simultaneously received knowledgeable and non-knowledgeable accountants. We further restrict our analysis to firms where we can observe at least two consecutive years before and after the accountant switch. Moreover, we focus on switches happening in 2010 or later so that in both years before the switch bunching was a viable option. This leaves us with a sample of only 3911 accountant switches. Table 14 shows descriptive statistics for this experts event study. Control and treatment firms are balanced along average key demographic and pre-event income variables.

Figure 9 graphically depicts the experts event study. The vertical axis denotes the average firm-level bunching share among treatment and control group respectively. The horizontal axis denotes event time relatively to the year of the incoming accountant (year 0). We observe stable pre-event trends between treatment and control group before the new accountant enters the firm. In the first year after the accountant switch we observe a clear difference between treatment and control firms. Control firms seem to have a significantly lower propensity to employ bunchers. However, in the second and third year at the new firm this effect is not very distinguishable anymore.

Table 15 denotes regression results from event-study type regressions analogous to equations (5) and (6) employed in quantifying the peer information transmission channel. The notable exception is that the outcome variable is now the firm-level bunching decision and the treatment indicator $treat_j$ indicates firm j receiving a knowledgeable accountant. While we find strong positive effects of receiving a knowledgeable accountant in our specification without controls, this effect is very small and not significant when including control variables. We rationalize this with the observation that in this rigorous event study design, we are drawing on a relatively small sample of accountant switches. The results of our event study point in the same direction as the strong effects of knowledgeable accountants observed in Table (9), however, due to sample restrictions they are not as strong and significant.

5 Conclusion

In this paper we analyze tax avoidance behavior using new administrative data on personal income taxes from Ecuador. Learning plays an important role in determining individual tax adjustments: as taxpayers gain experience in the formal sector, they are more likely to avoid paying taxes by positioning their taxable income just below the exemption threshold. This bunching is driven through reporting behavior based on generous deduction possibilities. By exploiting matched employer-employee data and a research design based on job switches, we find the firm environment to be crucial in determining individual learning processes about tax avoidance opportunities.

Furthermore, this paper exploits the strong rise in the size of the Ecuadorian formal sector to provide evidence for the importance of firm-level dynamics in bunching behavior. We show that the knowledge environment at the firm-level can be characterized by a binary indicator: either a firm has knowledge about bunching opportunities or it does not. Conditional on employing bunchers, the share of employees bunching remains relatively stable over time. The paper is able to identify and quantify two specific channels of information transmission that explain the rise in firm-level knowledge on bunching activity. We quantify the effects of peers and experts by exploiting changes in the coworker composition of firms and accountant switches.

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 and when they will translate into actual behavior, especially in a dynamically growing setting. Due to partial usage only by individuals in an advantageous knowledge environment, such reforms can also (at least in the short and medium run) increase inequality. Moreover, our analysis has shown the importance of firms and firm-level environments in driving the usage of tax avoidance opportunities. This observation is important when designing strategies to combat tax avoidance and setting up auditing targets.

In future research on behavioral responses to public policies, we think it is important to focus more strongly on dynamic aspects. Especially in settings with a growing number of affected parties or beneficiaries, these economic agents do not respond to incentives immediately and take time to understand and learn about the system. Moreover, identifying specific channels of information transmission can be informative for the design of optimal policies and to guide policymakers in improving existing ones.

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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***	1.36***	1.86***	2.88***	1.81***	3.34***	3.88***	4.44***	4.63***	5.18***	6.03***
	(0.24)	(0.37)	(0.36)	(0.49)	(0.61)	(0.54)	(0.58)	(0.72)	(0.91)	(0.77)	(0.61)
Gross Income	0.23	1.35***	1.85***	1.16**	-0.36	1.05	0.80	0.26	-0.36	-0.62	-0.33
	(0.29)	(0.38)	(0.36)	(0.59)	(0.81)	(0.75)	(0.75)	(0.94)	(1.04)	(0.99)	(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 estimates over time by cohort

Cohort	2007	2008	2009	2010	2011	2012	2013	2014	2015	Observations
Taxable Income										
2007	2.59*	2.95***	2.89***	3.08***	4.25***	4.98***	4.31***	4.93***	6.65***	48,570
	(1.50)	(1.08)	(1.08)	(0.77)	(0.74)	(0.70)	(0.58)	(0.60)	(0.65)	
2008		3.44**	-0.57	2.90***	2.64***	4.78***	3.08***	4.72***	3.83***	79,785
		(1.59)	(0.92)	(0.75)	(0.65)	(0.68)	(0.56)	(0.51)	(0.52)	
2009			0.26	0.75	2.26**	5.74***	4.34***	5.67***	5.61***	59,427
			(0.66)	(1.60)	(1.02)	(1.02)	(1.03)	(0.70)	(0.79)	
2010				0.62	2.16	3.94***	4.75***	5.45***	5.56***	67,024
				(0.98)	(1.74)	(1.21)	(1.19)	(1.00)	(0.82)	
2011					1.18	3.72*	6.05***	6.15***	7.19***	108,496
					(0.97)	(2.15)	(1.61)	(1.15)	(1.04)	
2012						2.91	4.64*	5.69***	5.49***	140,777
						(3.23)	(2.57)	(1.35)	(0.96)	
2013							5.21	4.08*	6.25***	168,952
							(3.43)	(2.19)	(1.38)	
2014								3.73	7.38***	219,543
								(3.07)	(1.78)	
Gross Income										
2007	2.56*	1.68	1.15	1.81*	1.59**	0.72	0.64	0.15	0.58	48,570
	(1.50)	(1.11)	(1.14)	(0.94)	(0.86)	(0.80)	(0.77)	(0.71)	(0.79)	
2008		1.85	-2.24**	1.06	0.98	1.50**	0.04	0.63	-0.46	79,785
		(1.68)	(1.03)	(0.79)	(0.76)	(0.76)	(0.63)	(0.64)	(0.61)	
2009			1.25	-1.54	-0.73	2.30**	0.05	0.55	-0.02	59,427
			(3.67)	(1.57)	(1.09)	(1.04)	(1.14)	(0.83)	(0.87)	
2010				1.28	-1.06	1.27	0.47	0.43	0.18	67,024
				(3.43)	(1.75)	(1.30)	(1.27)	(1.08)	(0.94)	
2011					0.20	-1.19	-0.87	-0.08	0.41	108,496
					(3.33)	(2.19)	(1.69)	(1.30)	(1.10)	
2012						-2.05	-0.78	-0.46	-1.06	140,777
						(3.28)	(2.65)	(1.52)	(1.13)	
2013							-2.57	-2.39	-0.89	168,952
							(3.36)	(2.36)	(1.35)	
2014								-3.72	-1.18	219,543
								(3.10)	(1.91)	

Note: This table reports bunching estimates for taxable and gross income by year conditioned on the cohort of entry into the formal economy. 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 4: Bunching Individuals

	(1)	(2)
	Probit Estimates for Bunching Indicator	
Income Experience	0.077***	0.068***
	(0.012)	(0.014)
Gross Income		0.00002***
		(0.00000)
Age		0.0065***
		(0.0023)
Female		0.11***
		(0.011)
Foreign		-0.0083
		(0.017)
Married		0.045***
		(0.0082)
Secondary Education		0.035*
		(0.020)
Tertiary Education		0.060**
		(0.028)
Observations	1050694	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, firmsize, 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 5: Job Switchers - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Mid to Low	Mid to Mid	Mid to High
Demographics				
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
Pre-Switch				
Gross Income	6165.42	6248.25	6311.41	6645.06
Taxable Income	5713.57	5811.62	5870.43	6156.23
Share Deduction Filers	0.08	0.07	0.07	0.08
Buncher	0.04	0.03	0.03	0.04
Post-Switch				
Gross Income	7559.51	5766.48	7747.27	8523.04
Taxable Income	6798.96	5398.47	7003.73	7497.14
Share Deduction Filers	0.14	0.08	0.12	0.20
Buncher	0.05	0.03	0.04	0.08
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 two years before the move, post-move the respective values in the first two years at the destination 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 6: Job Switchers

	(1)	(2)	(3)	(4)
	Mid to Low		Mid to High	
A. Overall Effect				
After event year	-0.008**	-0.002	0.036***	0.031***
	(0.004)	(0.004)	(0.005)	(0.005)
Panel B:				
Anticipatory Effects				
Event year - 2	0.004	0.003	0.004	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
Event year - 1	0.004	0.005	0.005	0.004
	(0.005)	(0.005)	(0.006)	(0.006)
Post Treatment Effects				
Event year	-0.009	-0.003	0.019**	0.015*
	(0.006)	(0.006)	(0.008)	(0.008)
Event year + 1	-0.003	0.003	0.054***	0.049***
	(0.007)	(0.007)	(0.008)	(0.008)
Event year + 2	0.000	0.006	0.050***	0.043***
	(0.008)	(0.008)	(0.010)	(0.010)
Controls	No	Yes	No	Yes
Observations	65186	65186	64473	64473
Panel C: Timing				
Event year - 1	-0.003	-0.001	-0.002	-0.006
	(0.003)	(0.005)	(0.004)	(0.008)
Event year	-0.002	0.006	0.025***	0.017
	(0.003)	(0.009)	(0.006)	(0.014)
Event year + 1	0.013***	0.021	0.070***	0.054**
	(0.005)	(0.014)	(0.006)	(0.023)
Controls	No	Yes	No	Yes
Observations	23542	23542	22662	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 7: Extensive Margin of Firm-level Bunching over time by cohort

	2008	2009	2010	2011	2012	2013	2014	2015	Obs
Cohort									
2008	0.20	0.31	0.38	0.41	0.53	0.61	0.63	0.67	489
	(0.40)	(0.46)	(0.49)	(0.49)	(0.50)	(0.49)	(0.48)	(0.47)	
2009		0.23	0.33	0.41	0.47	0.53	0.59	0.61	528
		(0.42)	(0.47)	(0.49)	(0.50)	(0.50)	(0.49)	(0.49)	
2010			0.21	0.31	0.43	0.51	0.56	0.54	555
			(0.41)	(0.46)	(0.50)	(0.50)	(0.50)	(0.50)	
2011				0.26	0.38	0.45	0.50	0.55	1100
				(0.44)	(0.49)	(0.50)	(0.50)	(0.50)	
2012					0.31	0.41	0.50	0.49	1657
					(0.46)	(0.49)	(0.50)	(0.50)	
2013						0.37	0.46	0.48	2203
						(0.48)	(0.50)	(0.50)	
2014							0.38	0.44	3280
							(0.48)	(0.50)	
2015								0.36	4847
								(0.48)	

Note: Share of firms in given cohort with at least one buncher. Cohorts conditioned on year of entry into formal sector and having potential bunchers in all subsequent years.

Table 8: Intensive Margin of Firm-level Bunching over time by firm cohort

		2008	2009	2010	2011	2012	2013	2014	2015
Cohort									
2008	Share	0.23	0.25	0.28	0.27	0.28	0.31	0.31	0.33
	SD	(0.20)	(0.20)	(0.25)	(0.20)	(0.22)	(0.23)	(0.23)	(0.24)
	Obs	21	58	86	100	142	165	195	187
2009	Share		0.26	0.26	0.24	0.29	0.29	0.28	0.27
	SD		(0.23)	(0.21)	(0.20)	(0.23)	(0.21)	(0.22)	(0.22)
	Obs		32	66	92	107	126	154	147
2010	Share			0.26	0.30	0.28	0.30	0.32	0.32
	SD			(0.14)	(0.22)	(0.23)	(0.22)	(0.25)	(0.24)
	Obs			23	60	74	109	134	127
2011	Share				0.32	0.30	0.30	0.33	0.34
	SD				(0.24)	(0.23)	(0.21)	(0.24)	(0.24)
	Obs				45	100	149	196	208
2012	Share					0.29	0.29	0.32	0.31
	SD					(0.22)	(0.21)	(0.23)	(0.24)
	Obs					60	124	209	224
2013	Share						0.34	0.34	0.37
	SD						(0.26)	(0.25)	(0.27)
	Obs						71	170	194
2014	Share							0.38	0.36
	SD							(0.27)	(0.27)
	Obs							99	165
2015	Share								0.36
	SD								(0.26)

Note: Share of bunchers among potential bunchers in given cohort, conditional on firms employing at least one buncher. Cohorts conditioned on year of entry into formal sector and having potential bunchers in all subsequent years. Further conditioned on firms employing at least 5 potential bunchers in given year. The number of observations varies between year of observation since the conditioning on having some buncher leads to a yearly changing composition of the cohort.

Table 9: Information Transmission between Firms: Extensive Margin

	Extensive Margin Bunching Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Incoming Buncher	0.11***	0.091***			0.11***	0.091***
	(0.023)	(0.024)			(0.023)	(0.024)
Knowledgeable Accountant			0.021**	0.055***	0.021**	0.055***
			(0.010)	(0.010)	(0.010)	(0.010)
Controls	No	Yes	No	Yes	No	Yes
Firm & year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34922	34922	34922	34922	34922	34922

Note: Controls: firm size, industry, region, lagged bunching behavior, and socio-demographic averages at firm-level. Standard errors clustered at firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Information Transmission between Firms: Intensive Margin

	Share of Bunchers among Potential Bunchers					
	(1)	(2)	(3)	(4)	(5)	(6)
Incoming Buncher	-0.020*	-0.018			-0.020*	-0.018
	(0.012)	(0.012)			(0.012)	(0.012)
Knowledgeable Accountant			-0.004	-0.000	-0.004	0.000
			(0.009)	(0.009)	(0.009)	(0.009)
Controls	No	Yes	No	Yes	No	Yes
Firm & year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7262	7262	7262	7262	7262	7262

Note: Controls: firm size, industry, region, lagged bunching behavior, and socio-demographic averages at firm-level. Standard errors clustered at firm level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Bunching Firms

	At least one buncher	
Share Married	-0.00091	(0.010)
Avg. Age	-0.0033***	(0.0003)
Share Female	0.043***	(0.007)
Between 25 and 250 Employees	0.098***	(0.004)
More than 250 Employees	0.27***	(0.045)
Sectors		
Manufacturing	0.084***	(0.007)
Construction	0.044***	(0.006)
Trade; Repairing	0.094***	(0.007)
Hotel and Restaurant	0.038***	(0.002)
Transport, Storage, Communication	0.061***	(0.007)
Financial Sector	0.16***	(0.009)
Real Estate, Business and Renting	0.079***	(0.008)
Education	0.057***	(0.008)
Health and Social Services	0.069***	(0.009)
Other	0.077***	(0.007)
Observations	34922	

The table reports results from an OLS regression at the firm level with an indicator for bunching employees as the dependent variable. On average 43% of the firms in this sample employ bunchers. Subsample of firms with potential bunchers in years 2008-2015. Further (unreported) control variables include share tertiary education and average gross income. 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.

Table 12: Peer Learning Event Study - Descriptives

	(1) Full Sample	(2) Control	(3) Treatment
Demografics			
Avg. Age	36.02	36.00	36.21
Share Married	0.52	0.52	0.53
Share Female	0.37	0.37	0.40
Share Tertiary Education	0.32	0.32	0.33
Firmsize	50.74	50.68	51.24
Pre-Event			
Avg. Gross Income	6903.01	6792.00	7748.11
Avg. Taxable Income	6231.00	6142.75	6902.77
Share Deduction Filers	0.13	0.12	0.16
Share Buncher	0.06	0.05	0.08
Observations	2954	2611	343

Notes: This table shows descriptive statistics for the sample of firms used for quantifying the peer channel. 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 13: Peer Learning - Regression Results

	(1)	(2)
Panel A: Overall Effect		
DiD estimate	0.052**	0.047**
	(0.022)	(0.022)
Panel B:		
Anticipatory Effects		
Event year - 2	0.016	0.018
	(0.029)	(0.029)
Event year - 1	0.010	0.011
	(0.033)	(0.033)
Post Treatment Effects		
Event year	0.041	0.037
	(0.033)	(0.034)
Event year + 1	0.077**	0.074**
	(0.035)	(0.035)
Event year + 2	0.071	0.067
	(0.044)	(0.044)
Controls	No	Yes
Observations	15913	15913

The table reports results from regression equations (5) and (6) at the firm level. Outcome variable is the leave-out firm bunching decision 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, as well as industry and province dummies. Standard errors (in parentheses) are clustered at the firm level. Significance levels are given by * < 0.1, ** < 0.05, and *** < 0.01.

Table 14: Experts Event Study - Descriptives

	(1) Full Sample	(2) Control	(3) Treatment
Demographics			
Avg. Age	39.23	39.36	38.84
Share Married	0.62	0.63	0.60
Share Female	0.40	0.40	0.41
Share Tertiary Education	0.51	0.52	0.49
Firmsize	93.61	89.67	102.55
Pre-Event			
Avg. Gross Income	13790.07	13785.67	13751.39
Avg. Taxable Income	11107.28	11161.65	10922.79
Share Deduction Filers	0.58	0.57	0.62
Share Buncher	0.19	0.19	0.22
Observations	3911	2577	1019

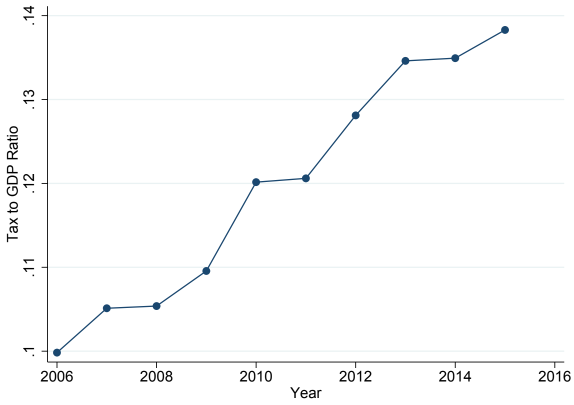
Notes: This table shows descriptive statistics for the sample of firms used for quantifying the experts channel. Control refers to firms receiving an accountant previously working at a firm with potential bunchers but with zero bunching employees, treatment refers to firms receiving new accountants previously working at a firm with bunching employees. Pre-event refers to the year before the arrival of the new accountant.

Table 15: Experts Event Study - Regression Results

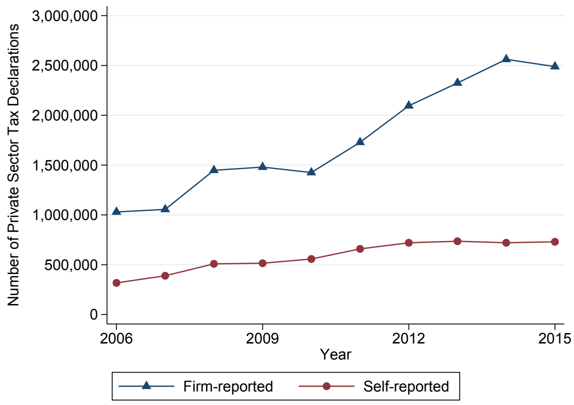
	(1)	(2)
Panel A: Overall Effect		
DiD estimate	0.132***	-0.013
	(0.018)	(0.023)
Panel B: ***Anticipatory Effects***		
Event year - 2	0.057*	-0.010
	(0.031)	(0.039)
Event year - 1	0.131***	0.002
	(0.032)	(0.039)
Post Treatment Effects		
Event year	0.174***	0.000
	(0.030)	(0.039)
Event year + 1	0.234***	-0.020
	(0.033)	(0.040)
Event year + 2	0.263***	-0.034
	(0.039)	(0.046)
Controls	No	Yes
Observations	11926	11926

The table reports results from the event study regressions quantifying the experts channel detailed in Section (4.2.2). Outcome variable is an indicator whether a firm employs a buncher or not, event year refers to the year of the accountant switch. The treatment is given by a firm receiving a knowledgeable accountant. Firm and year fixed effects are included throughout. We control for average income, share tertiary educated, average age, share married, share female, firmsize, as well as industry and province dummies. Standard errors (in parentheses) are clustered at the firm 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

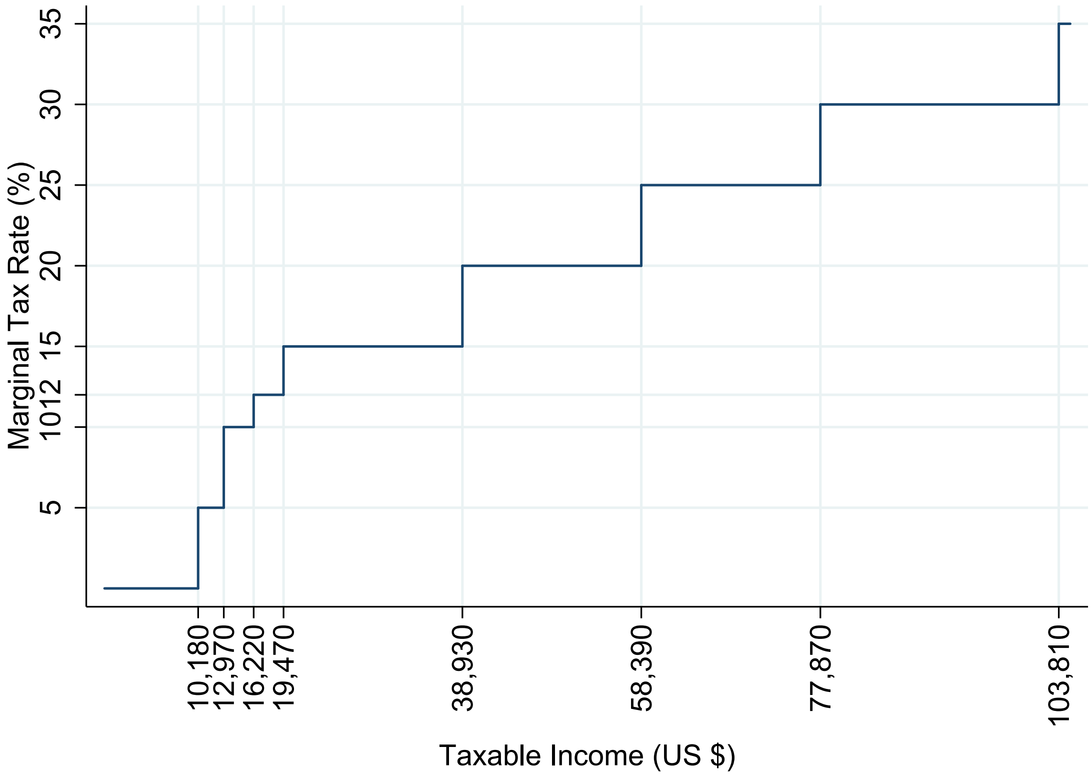


Figure 3: Binned Gross Income

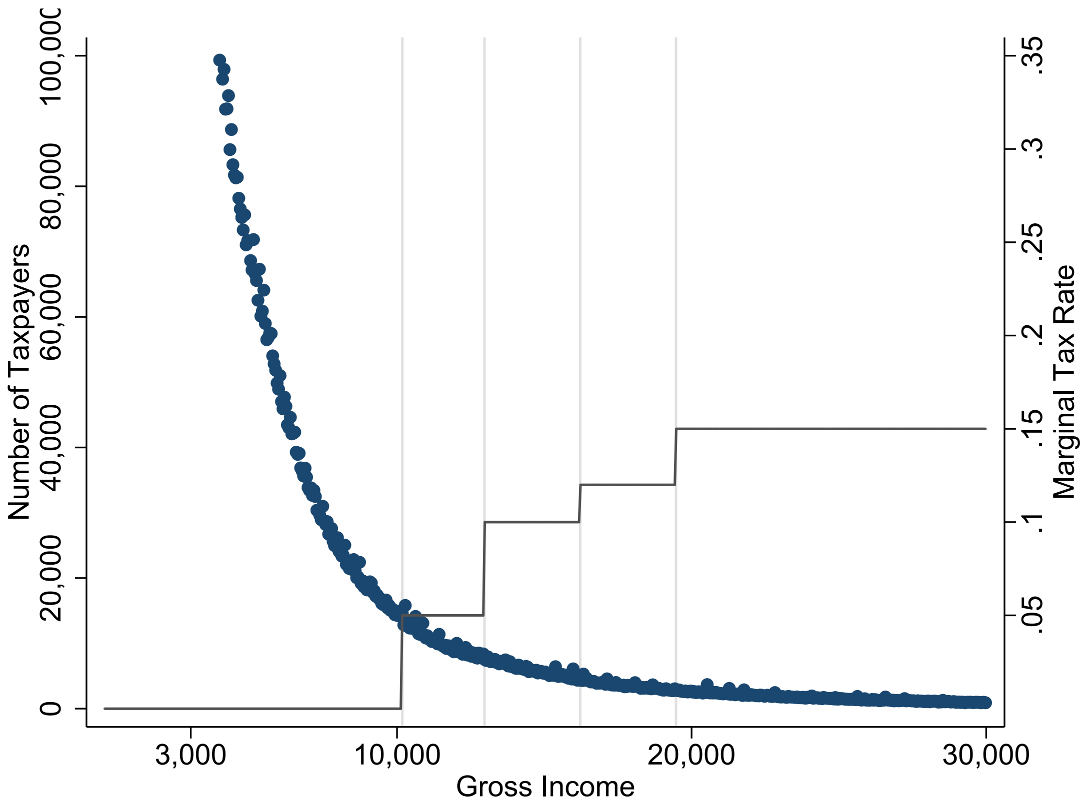


Figure 4: Binned Taxable Income

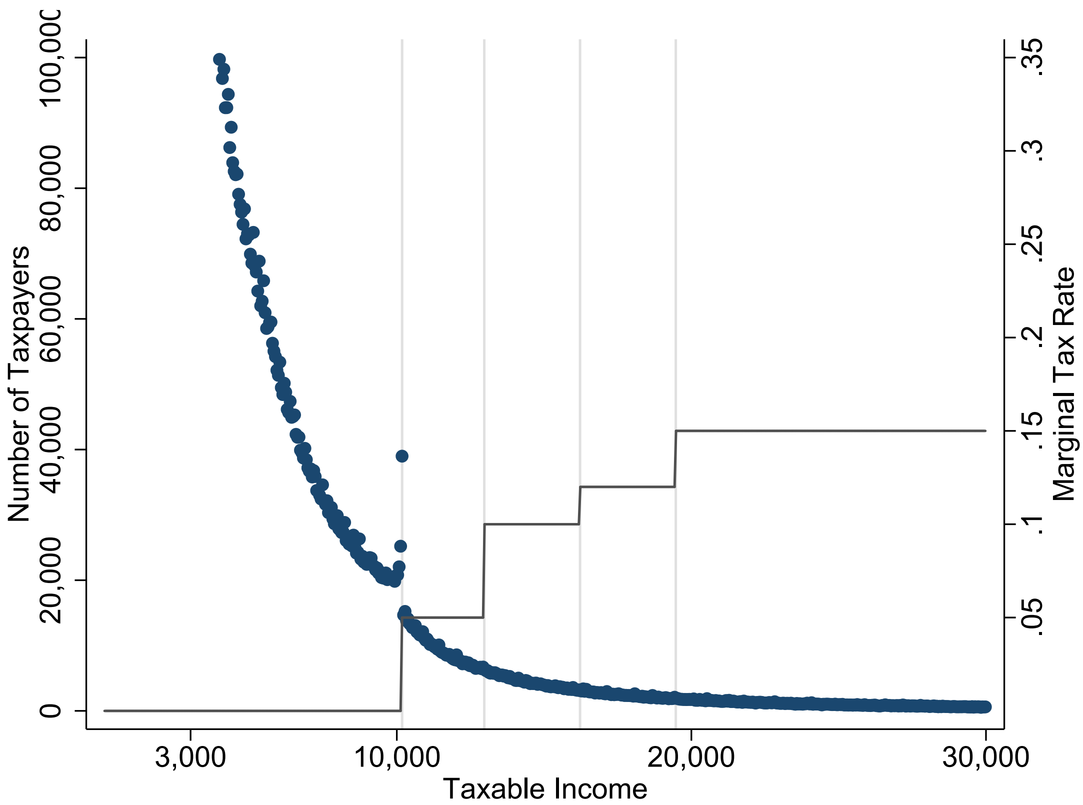


Figure 5: Number of Employees

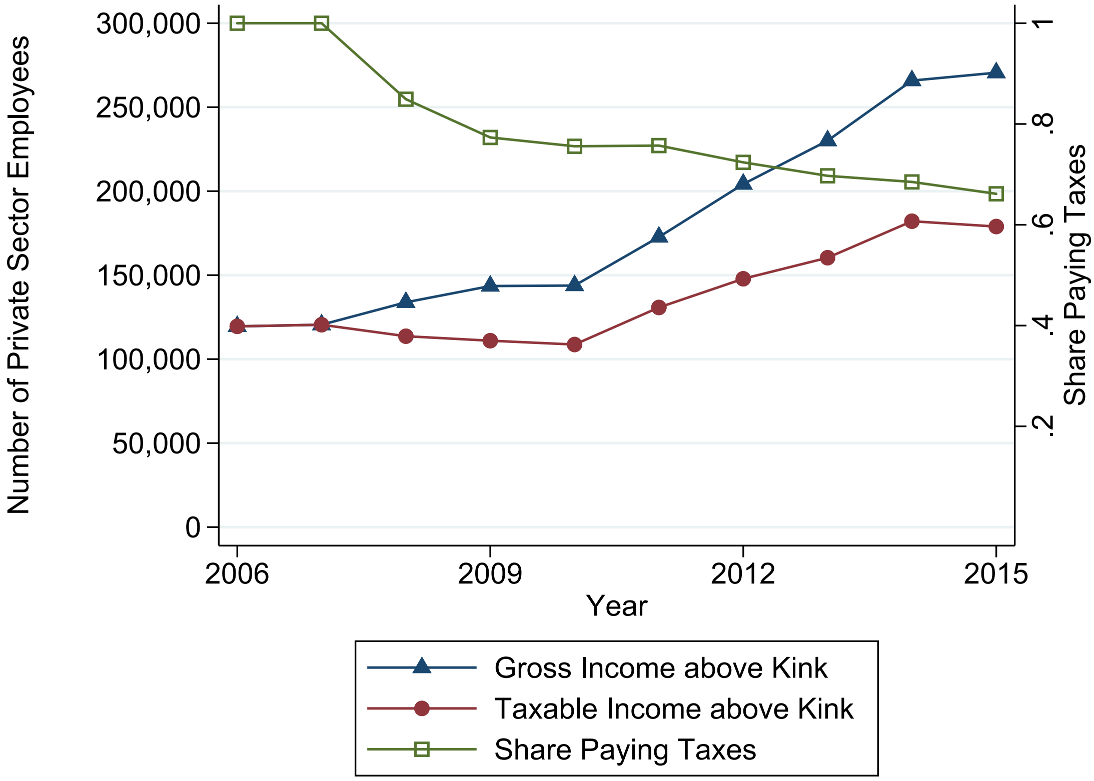


Figure 6: Bunching Estimates Taxable Income

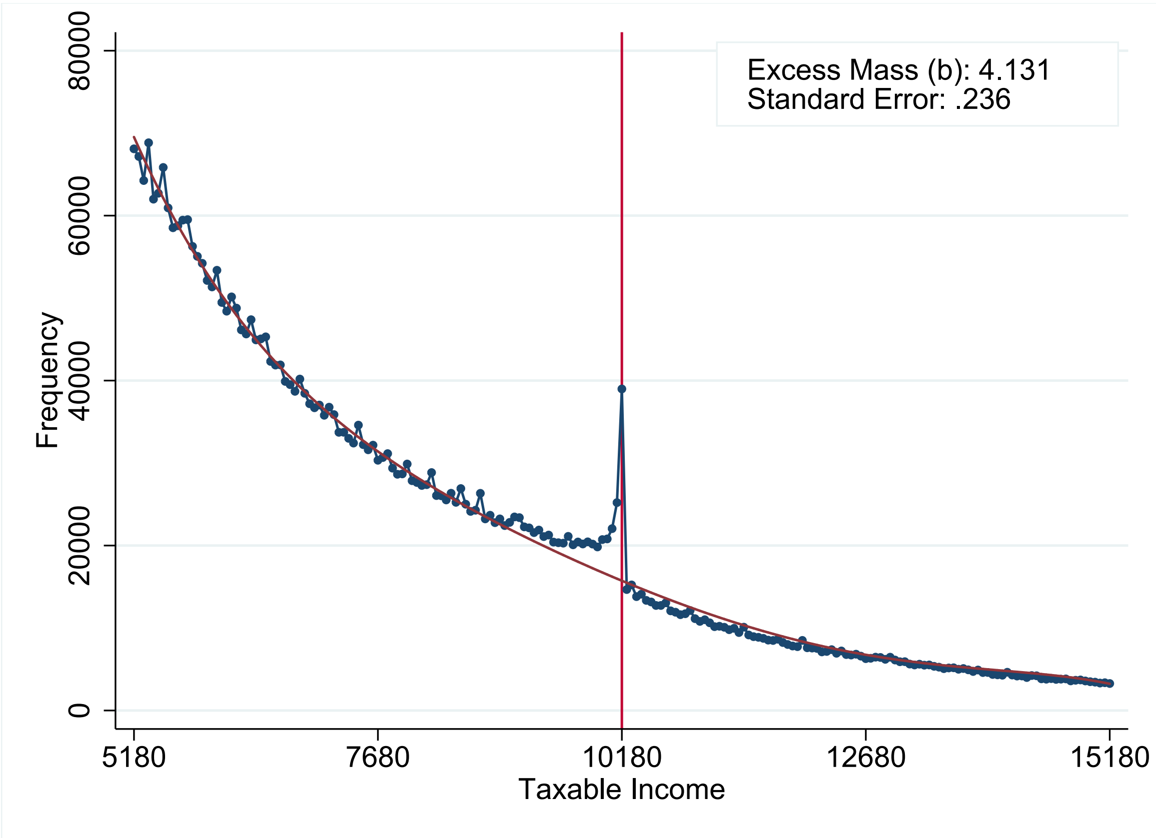


Figure 7: Event Study Job Switchers

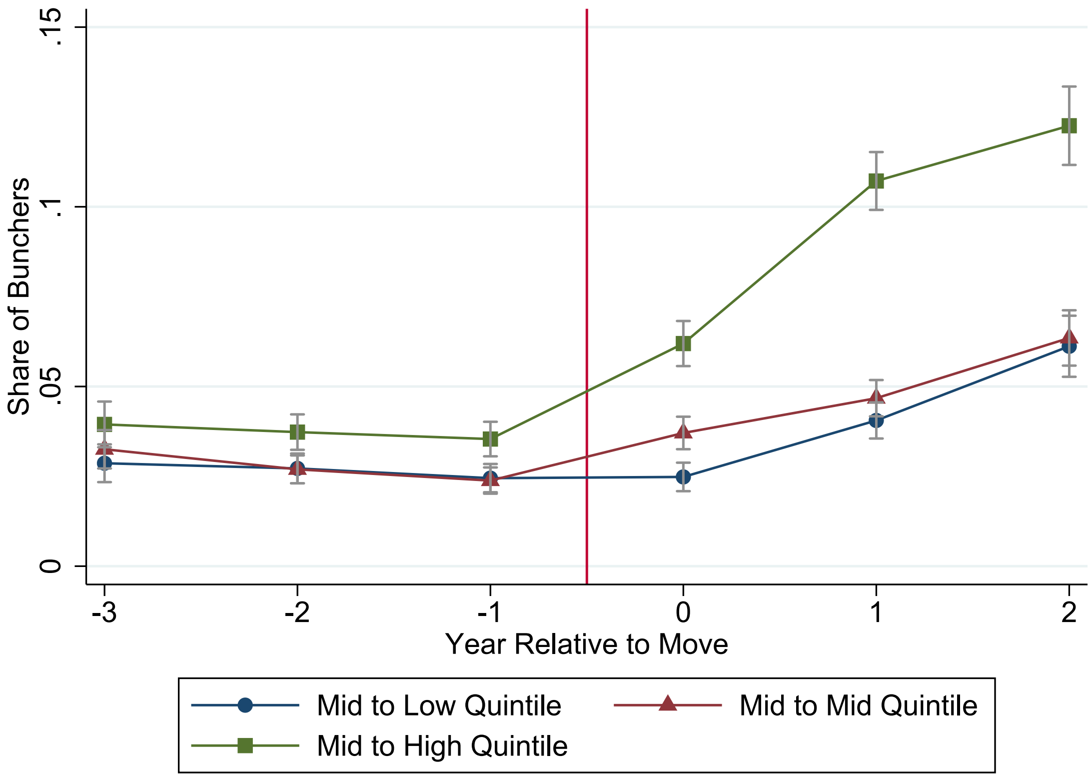


Figure 8: Peer Learning Event Study

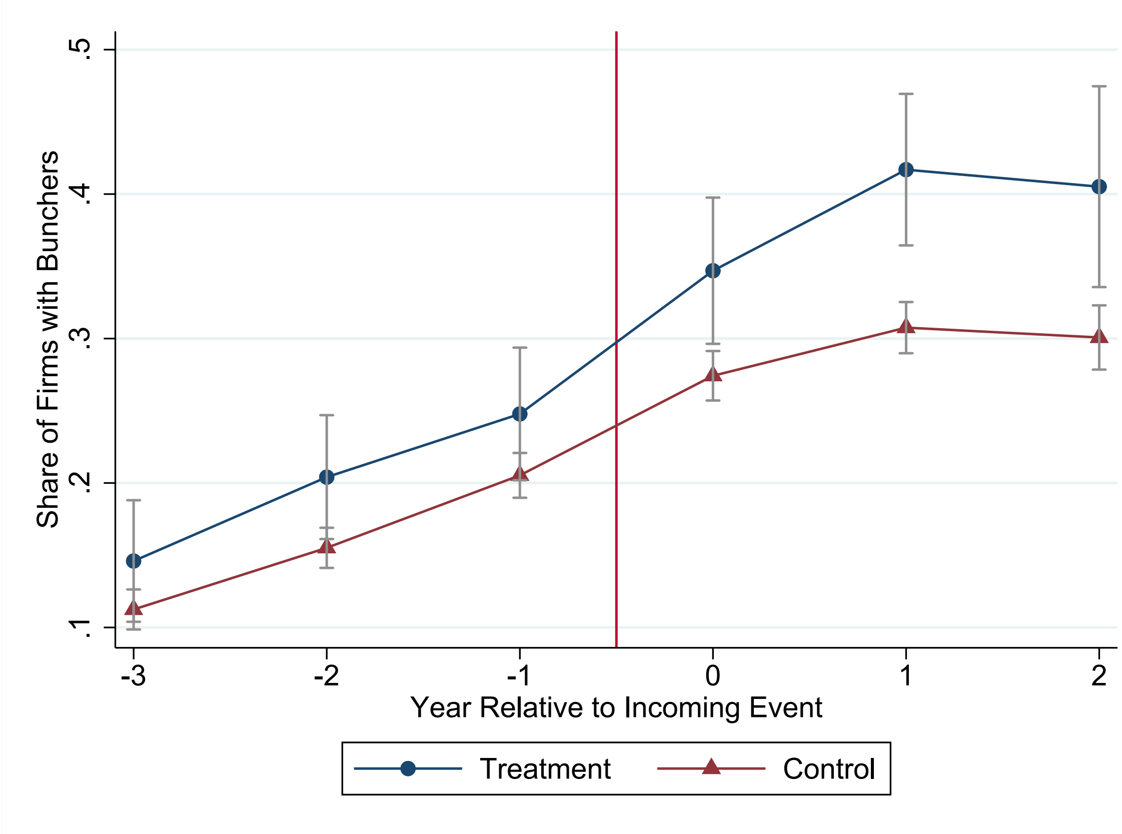
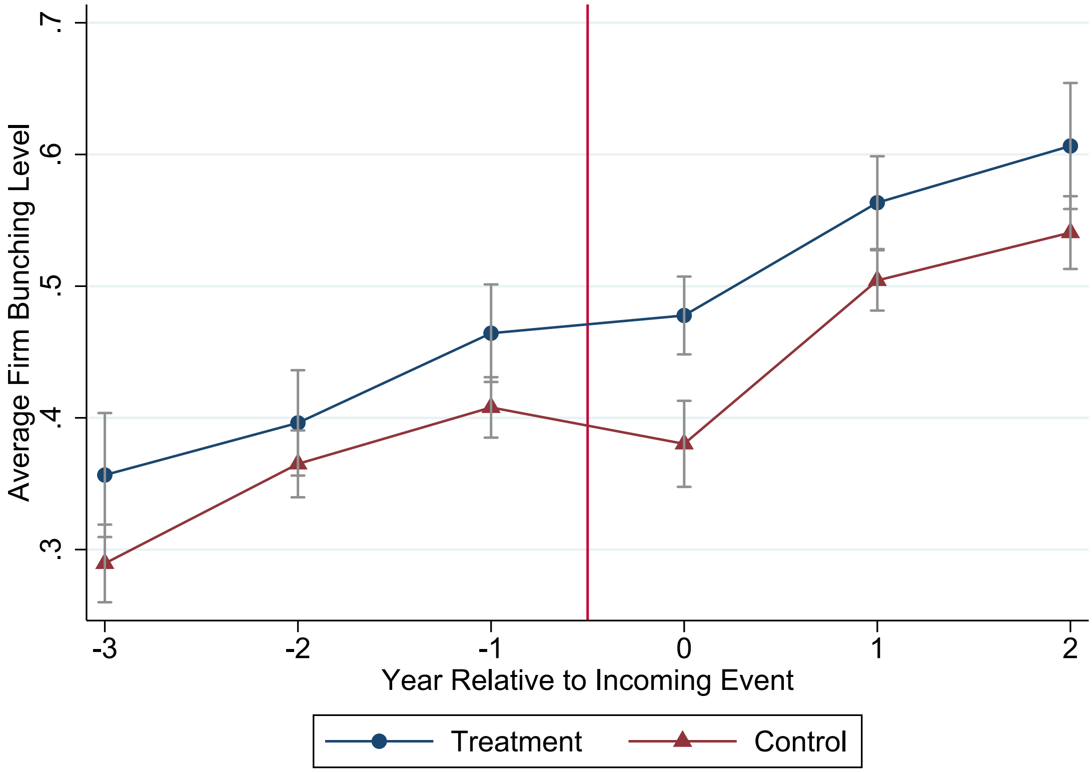


Figure 9: Experts Event Study



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 exemption threshold. 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 large parts of the literature, 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.

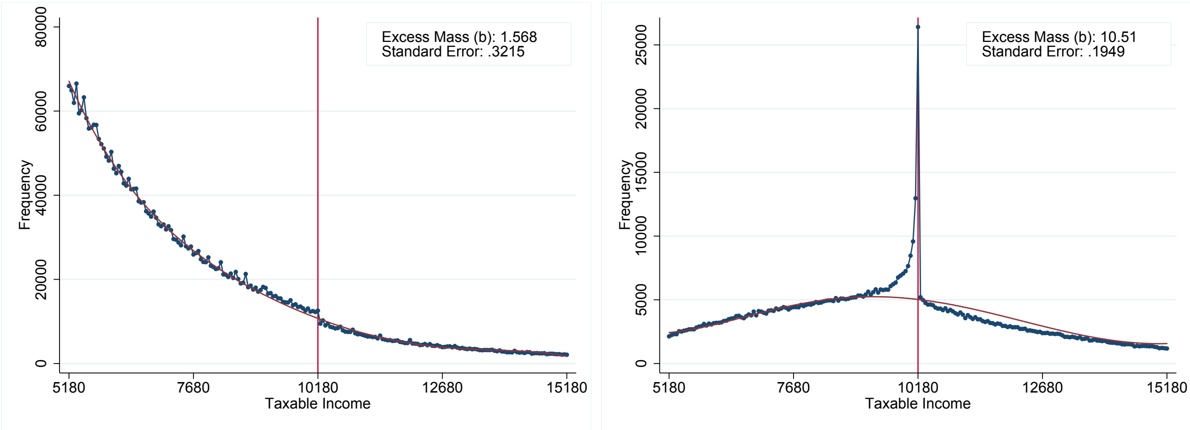
In the job switcher analysis in Section 4.1.2, the asymmetry of the response is further emphasized by the evidence in Figure A.2. The left panel shows bunching shares among workers who start from a firm in the lower quintile of the bunching distribution while

Table A1: Job Switchers Potential Buncher

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

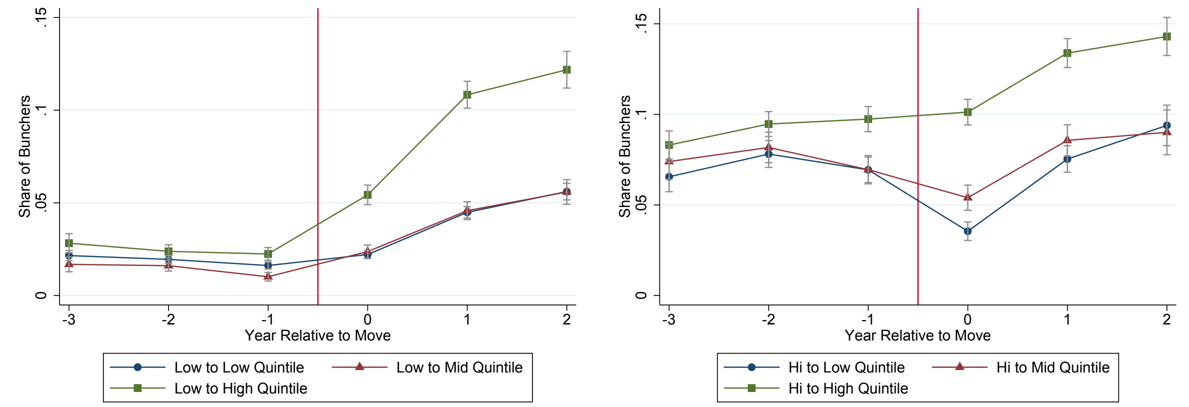
This table reports results for a reduced version of the job-switcher sample from Table 6. The sample is restricted to potential bunchers with gross earnings between 10180 and 20360 USD, that is individuals who can use their deductions to reduce their annual income below the threshold for paying taxes. 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.1: The impact of filing deductions



(a) No Deductions (b) With Deductions

Figure A.2: Event Study Job Switchers



(a) from low bunching (b) from high bunching 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 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.

Figure A.3: Tax Declaration Form F107 for Wage Earners

FORMULARIO 107 RESOLUCIÓN No. NAC-DGERCGC12-00829	COMPROBANTE DE RETENCIONES EN LA FUENTE DEL IMPUESTO A LA RENTA POR INGRESOS DEL TRABAJO EN RELACIÓN DE DEPENDENCIA			No.	
	EJERCICIO FISCAL	102	FECHA DE ENTREGA	103	AÑO / MES / DIA

100 Identificación del Empleador (Agente de Retención)

105	RUC 0 0 1	106	RAZÓN SOCIAL O APELLIDOS Y NOMBRES COMPLETOS

200 Identificación del Trabajador (Contribuyente)

201	CÉDULA O PASAPORTE	202	APELLIDOS Y NOMBRES COMPLETOS

Liquidación del Impuesto

SUELDOS Y SALARIOS	301	+	
SOBRESUELDOS, COMISIONES, BONOS Y OTROS INGRESOS GRAVADOS	303	+	
PARTICIPACIÓN UTILIDADES	305	+	
INGRESOS GRAVADOS GENERADOS CON OTROS EMPLEADORES	307	+	
DÉCIMO TERCER SUELDO	311		
DÉCIMO CUARTO SUELDO	313		
FONDO DE RESERVA	315		
OTROS INGRESOS EN RELACIÓN DE DEPENDENCIA QUE NO CONSTITUYEN RENTA GRAVADA	317		
(-) APORTE PERSONAL IESS CON ESTE EMPLEADOR (únicamente pagado por el trabajador)	351	-	
(-) APORTE PERSONAL IESS CON OTROS EMPLEADORES (únicamente pagado por el trabajador)	353	-	
(-) DEDUCCIÓN GASTOS PERSONALES - VIVIENDA	361	-	
(-) DEDUCCIÓN GASTOS PERSONALES - SALUD	363	-	
(-) DEDUCCIÓN GASTOS PERSONALES - EDUCACIÓN	365	-	
(-) DEDUCCIÓN GASTOS PERSONALES - ALIMENTACIÓN	367	-	
(-) DEDUCCIÓN GASTOS PERSONALES - VESTIMENTA	369	-	
(-) EXONERACIÓN POR DISCAPACIDAD	371	-	
(-) EXONERACIÓN POR TERCERA EDAD	373	-	
IMPUESTO A LA RENTA ASUMIDO POR ESTE EMPLEADOR	381	+	
BASE IMPONIBLE GRAVADA **301+303+305+307-351-353-361-363-365-367-369-371-373+381 ≥ 0**	399	=	
IMPUESTO A LA RENTA CAUSADO	401	=	
VALOR DEL IMPUESTO RETENIDO Y ASUMIDO POR OTROS EMPLEADORES DURANTE EL PERÍODO DECLARADO	403		
VALOR DEL IMPUESTO ASUMIDO POR ESTE EMPLEADOR	405		
VALOR DEL IMPUESTO RETENIDO AL TRABAJADOR POR ESTE EMPLEADOR	407		
INGRESOS GRAVADOS CON ESTE EMPLEADOR (informativo) 301+303+305+381	349	=	

IMPORTANTE: Sírvase leer cada una de las siguientes instrucciones.

1.- El trabajador que, en el mismo período fiscal haya reiniciado su actividad con otro empleador, estará en la obligación de entregar el formulario 107 entregado por su anterior empleador a su nuevo empleador, para que aquel, efectúe el cálculo de las retenciones a realizarse en lo que resta del año.

2.- El campo 307 deberá ser llenado con la información registrada en el campo 349 del Formulario 107 entregado por el anterior empleador, y/o con la proyección de ingresos de otros empleadores actuales, en caso de que el empleador que registra y entrega el presente formulario haya efectuado la retención por los ingresos percibidos con éstos últimos.

3.- La deducción total por gastos personales no deberá superar el 50% del total de ingresos gravados, y en ningún caso será mayor al equivalente a 1.3 veces la fracción básica exenta de Impuesto a la Renta de personas naturales.

4.- 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.

5.- El trabajador deberá presentar el Anexo de Gastos Personales que deduzca, de cumplir las condiciones establecidas por el Servicio de Rentas Internas.

6.- De conformidad con la Resolución No. NAC-DGER2008-0566 publicada en el Registro Oficial No. 342 el 21 de mayo del 2008, el beneficio de la exoneración por tercera edad se configura a partir del ejercicio en el cual el beneficiario cumpla los 65 años de edad. El monto de la exoneración será el equivalente al doble de la fracción básica exenta de Impuesto a la Renta.

7.- A partir del año 2013, conforme lo dispuesto en la Ley Orgánica de Discapacidades el monto de la exoneración por discapacidad será el equivalente al doble de la fracción básica exenta de Impuesto a la Renta.

8.- El presente formulario constituye la declaración de Impuesto a la Renta del trabajador, siempre que durante el período declarado la persona únicamente haya prestado sus servicios en relación de dependencia con el empleador que entrega este formulario, y no existan valores de gastos personales que deban ser reliquidados. En caso de pérdida de este documento el trabajador deberá solicitar una copia a su empleador.
Por el contrario, el trabajador deberá presentar obligatoriamente su declaración de Impuesto a la Renta cuando haya obtenido rentas en relación de dependencia con dos o más empleadores o haya recibido además de su remuneración ingresos de otras fuentes como por ejemplo: rendimientos financieros, arrendamientos, ingresos por el libre ejercicio profesional, u otros ingresos, los cuales en conjunto superen la fracción básica exenta de Impuesto a la Renta de personas naturales, o cuando tenga que reliquidar gastos personales con aquellos efectivamente incurridos, teniendo presente los límites referidos en las notas 3 y 4 de este documento.

DECLARO QUE LOS DATOS PROPORCIONADOS EN ESTE DOCUMENTO SON EXACTOS Y VERDADEROS, POR LO QUE ASUMO LA RESPONSABILIDAD LEGAL QUE DE ELLA SE DERIVEN (Art. 101 de la L.R.T.I.)

FIRMA DEL AGENTE DE RETENCIÓN	FIRMA DEL TRABAJADOR CONTRIBUYENTE	FIRMA DEL CONTADOR
		199 RUC CONTADOR 0 0 1

Figure A.4: Tax Declaration Form for Projecting Decuctions

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FORMULARIO SRI-GP

DECLARACIÓN DE GASTOS PERSONALES A SER UTILIZADOS POR EL EMPLEADOR EN EL CASO DE INGRESOS EN RELACION DE DEPENDENCIA

EJERCICIO FISCAL	**2 0 1 5**	**CIUDAD Y FECHA DE ENTREGA/RECEPCION**	**CIUDAD**	**AÑO**	**MES**	**DIA**
			QUITO			

Información / Identificación del empleado contribuyente (a ser llenado por el empleado)

101	CEDULA O PASAPORTE	102	APELLIDOS Y NOMBRES COMPLETOS

INGRESOS GRAVADOS PROYECTADOS (sin decimotercera y decimocuarta remuneración) (ver Nota 1)

(+) 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$	
(=) TOTAL INGRESOS PROYECTADOS	105	**USD$**	

GASTOS PROYECTADOS

(+) 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$	
(=) TOTAL GASTOS PROYECTADOS **(ver Nota 2)**	111	**USD$**	

NOTAS:

1.- Cuando un contribuyente trabaje con DOS O MÁS empleadores, presentará este informe al empleador con el que perciba mayores in gresos, 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.

Identificación del Agente de Retención (a ser llenado por el empleador)

112	RUC 1 7 6 0 0 1 3 2 1 0 0 0 1	113	RAZON SOCIAL, DENOMINACION O APELLIDOS Y NOMBRES COMPLETOS **SERVICIO DE RENTAS INTERNAS**

Firmas

EMPLEADOR / AGENTE DE RETENCION	**EMPLEADO CONTRIBUYENTE**
	FIRMA DEL SERVIDOR

Figure A.5: Bunching Estimates Gross Income

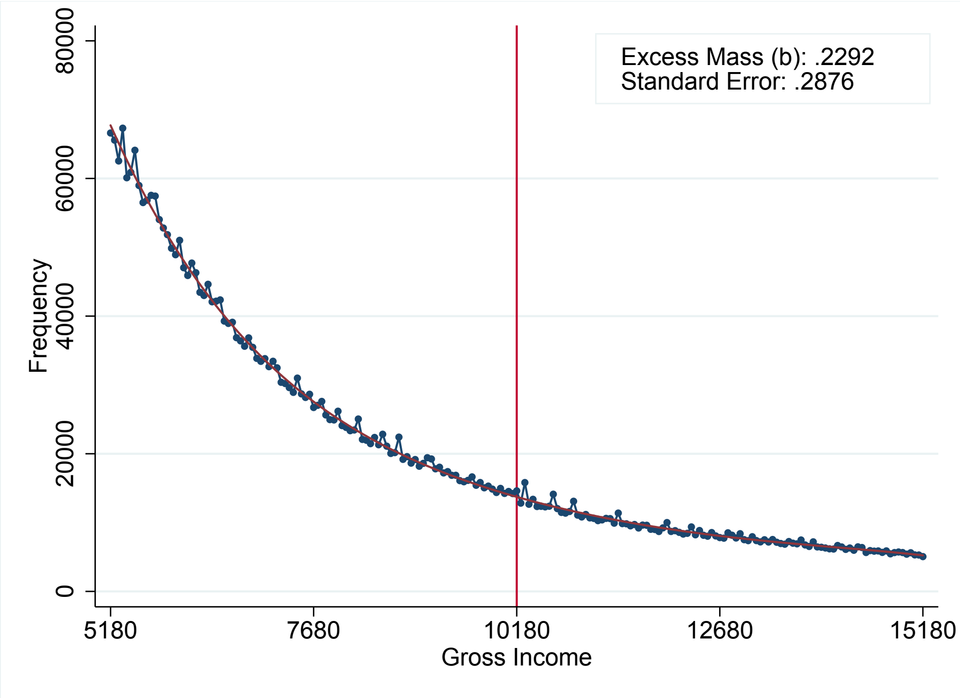
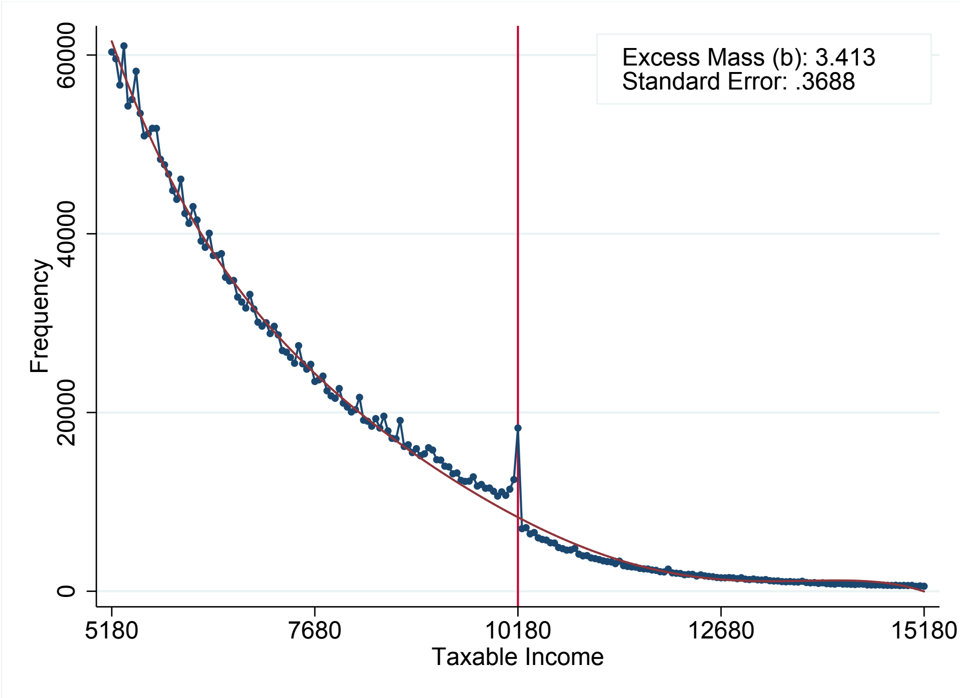
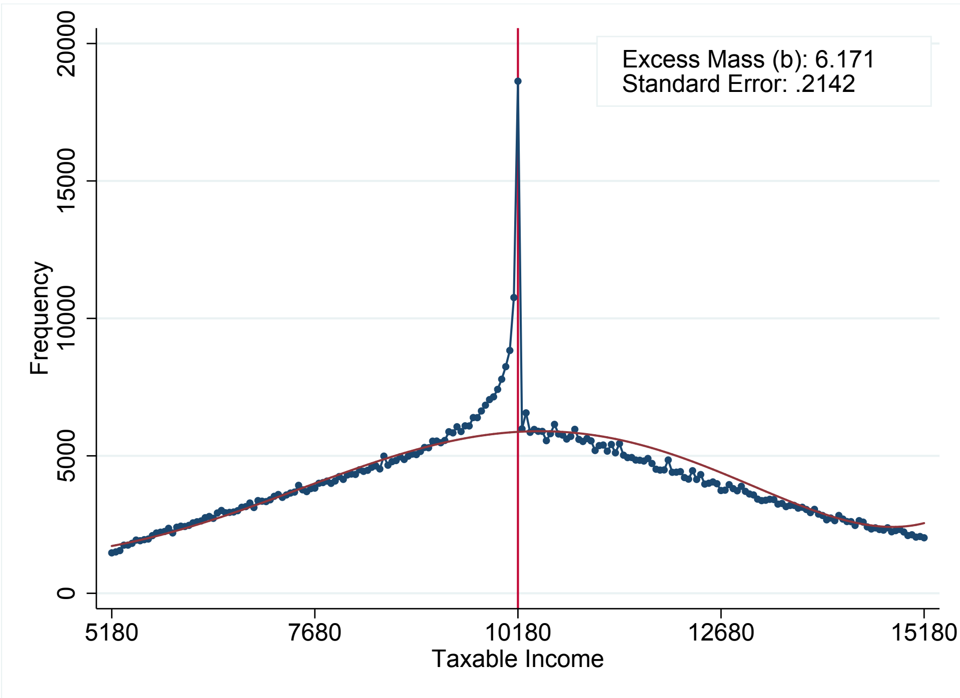


Figure A.6: Experience in paying taxes

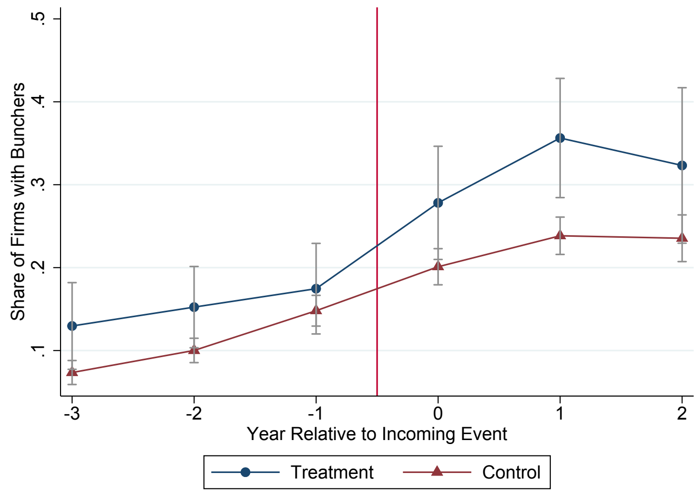


(a) No gross income above first kink in previous 2 years

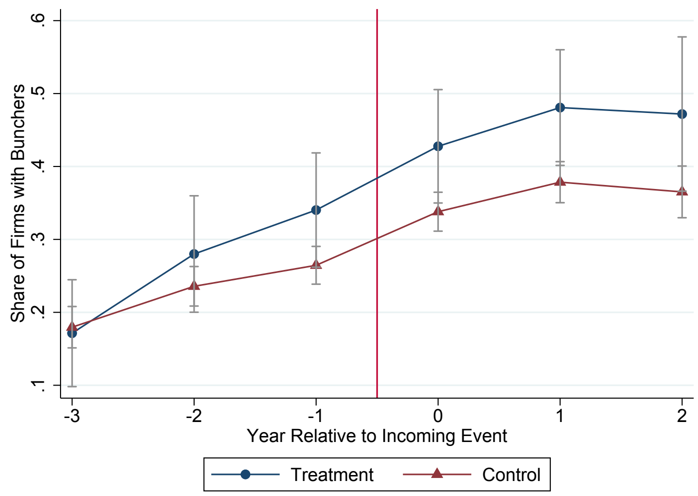


(b) At least one year of gross income above first kink in previous 2 years

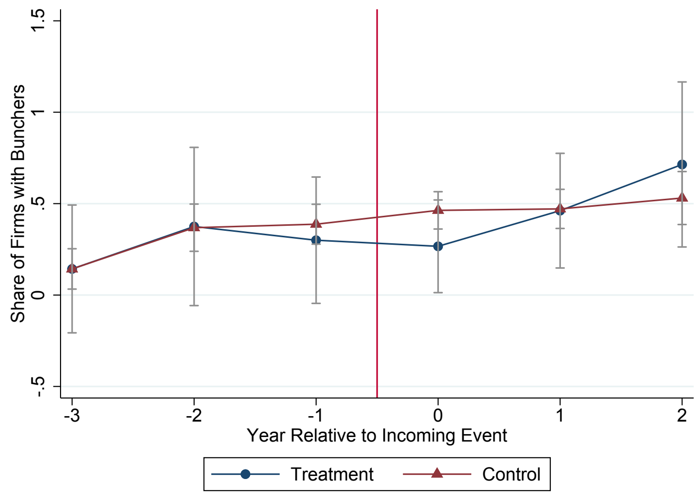
Figure A.7: Peer Learning Event Study - Firm Size



(a) Small Firms



(b) Medium Sized Firms



(c) Large Firms