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Albrecht Bohne
University of Mannheim

Jan Sebastian Nimczik
Humboldt University Berlin and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Information Frictions and Learning Dynamics: Evidence from Tax Avoidance in Ecuador*

We show how experience and dynamic learning processes reduce the obstacles to optimization imposed by information frictions when individuals newly enter the formal sector economy. Most importantly, we provide causal evidence on the exact mechanisms through which individuals learn about the functioning of government programs. To this aim, we exploit novel and rich administrative data on the universe of taxpayers in Ecuador and the introduction of generous tax deduction policies. Key to the identification of information transmission is exogenous worker mobility between firms. We find that the spread of information is driven by mobility of managers and tax experts.

JEL Classification: D83, H24, H26, H32, O17

Keywords: learning, tax avoidance, information frictions, taxation and development, bunching, behavioral responses to taxation

Corresponding author:
Jan Sebastian Nimczik
Humboldt University Berlin
Spandauer Str. 1
10178 Berlin
Germany

E-mail: jan.nimczik@hu-berlin.de

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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). A primary barrier to formalization is the lack of information about the functioning of government programs according to survey evidence from the World Bank (Perry, Maloney, Arias, Fajnyzlber, Mason, and Saavedra, 2007). While a growing literature looks 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 adapt to the formal system and try to learn about its incentives. This is particularly relevant in the context of behavioral responses to – often complicated – tax incentives. Previous work has extensively explored the role of adjustment frictions in constraining responses to the tax system (Chetty, Friedman, Olsen, and Pistaferri, 2011).[1] We are the first to thoroughly study the role of information frictions and how dynamic learning processes remove these obstacles. A number of studies have explored general spillovers between taxpayers (Chetty, Friedman, and Saez, 2013; Paetzold and Winner, 2016), but there is no clear consensus on how information frictions can be overcome. While a specific intervention teaching the tax code to EITC recipients in the US has proven to be rather ineffective (Chetty and Saez, 2013), we show that dynamic adjustments and learning processes lead to substantial changes in reported taxable income. Worker mobility is the most important driver of information transmission. We identify co-workers and accountants as specific channels of information transmission and show that information about tax adjustment opportunities spreads through top-down learning processes induced by job switches of managers and accountants.

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. Ecuador's rapidly formalizing economy with a steady inflow of new workers and firms to the tax system provides a unique setting to study dynamic information flows between taxpayers. We make four main contributions: First, we document dynamic developments of individual tax avoidance. With increasing tenure in the formal sector, individuals are more likely to avoid paying taxes. Second, we exploit exogenous job mobility to show that the increase in tax avoidance is causally affected by changes in the information environment individuals face. Third, we show that knowledge about tax avoidance opportunities spreads across firms and document that firms with more experience in the formal sector are more likely to have employees who avoid tax payments.

[1] Moreover, an emerging literature highlights the influence of behavioral biases on responses to tax incentives (Bhargava and Manoli, 2015; Taubinsky and Rees-Jones, ming; Benzarti, 2017).

Fourth, we identify specific channels of information transmission: peers (co-workers) and experts (accountants). In particular, we show that the learning process within firms is driven by top-down information transmission. Incoming co-workers in the top decile of a firm's wage distribution have a lasting effect on the tax avoidance behavior of their new co-workers. Likewise, introducing a knowledgeable accountant into a firm increases the tax adjustment behavior of the firm's employees.

Tax avoidance in Ecuador is mostly achieved by filing deductions for personal expenses in housing, health, nutrition, education, and clothing. Generous deduction possibilities are one of the government's main policies to induce an increase in formalization stimulating the demand for formal receipts. Strikingly, however, many individuals do not capitalize on the 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.[2] This low usage of easily accessible tax adjustment opportunities speaks to the presence of information frictions.

Our main measure of tax avoidance is the extent to which workers use deductions to lower their reported taxable income just below the income tax exemption threshold ("bunching"). We find a large and pronounced spike in the distribution of taxable income at the tax exemption threshold while the distribution of gross income (before using deductions) is smooth around all discontinuities in the marginal tax schedule. In extensive robustness analyses, we replicate all our results for alternative measures of tax avoidance without substantial change in the results.[3]

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 tax avoidance among cohorts of taxpayers by their year of entry into the formal sector. We find clear evidence of individual-level learning: across all cohorts, tax avoidance becomes stronger as individuals gain experience in the formal sector. We approximate the effect of experience through flexible polynomials and find strong initial increases in tax avoidance which level off after about five years in the formal system. We conclude that, with tenure in the formal sector, workers in Ecuador learn how to avoid paying taxes. The correlation between experience and avoidance remains strong and unchanged when controlling for a broad range of observable characteristics and unobserved

[2] 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.

[3] The first alternative measure tracks taxpayers lowering their taxable income to any value below the income tax exemption threshold while having gross income above the threshold, and the second measure indicates taxpayers using deductions at any position in the income distribution. Please refer to the supplemental online Appendix C for replications of our whole analysis.

heterogeneity.

However, it is unclear exactly *how* workers learn about the tax system. We provide causal evidence on how the information environment in firms drives individual learning processes. Exploiting the matched employer-employee component of our data, we identify asymmetric responses to exogenous changes in an individual's knowledge environment due to job transitions. Individuals moving into a firm with high levels of tax avoidance are more likely to avoid paying taxes themselves while individuals moving into a firm with low levels are just as likely to avoid paying taxes as before. These findings are robust to several identification strategies and can be interpreted as causal evidence that confirms the hypothesis of learning and memory in the literature (Chetty et al., 2013; Paetzold and Winner, 2016).

The importance of the firm environment in shaping individual learning processes motivates our interest in the firm-level dynamics of expanding the formal sector. We show that firms themselves are more likely to employ workers who avoid tax payments 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 prevalence of tax avoidance. However, once a firm engages in tax avoidance the *level* of tax avoidance within the firm remains relatively stable over time. We conclude that for firms information about tax avoidance practices is either 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 co-workers coming into a firm and the knowledge they bring about tax avoidance due to their behavior in the previous job. The experts channel is characterized by knowledgeable accountants who were previously working for a firm that was employing tax avoiders. We identify these effects through changes in the co-worker composition and switches of accountants. Both the peers and experts channels are sizeable, leading to average increases in firm-level avoidance 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 employees in firms with new co-workers that were previously avoiding are significantly more likely to avoid tax payments than incumbents among firms with new workers that were previously not avoiding. Likewise, firms with new accountants previously at a firm with no tax avoidance activity are less likely to avoid than those with new accountants with tax avoidance at their previous firm.

Our findings are highly policy relevant since they give indications for tax authorities in designing audit strategies and deciding who should be targeted. Moreover, in settings where a policy instrument is only partially used by economic agents, slow adjustments can have distributional implications. In our setting, the usage of the deduction opportunities is strongly related to advantaged demographic characteristics and firms in particular sectors. This increases inequality compared to a scenario with full adoption. A flexible labor market mitigates these information frictions by enhancing information transmission through job mobility.

Literature Our main contribution is towards the small but growing literature on 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 emphasize the role of learning. In contrast to these papers, however, we provide extensive evidence that the effects are not driven by selection into specific knowledge environments but are indeed causal. We establish causality of the knowledge environment by exploiting exogenous job mobility through firm closures, controlling for a broad range of observed and unobserved confounders, and additionally creating a balanced control group by matching on observables. Moreover, we extend this literature by exploring the dynamic learning processes and by identifying specific channels of information transmission. In a recent contribution, Akcigit, Aghion, Lequien, and Stantcheva (2017) show that sluggish adjustments to newly introduced tax regimes are also present in a developed country, France.

Our results are embedded in a broader literature that has established the importance of job mobility for the transmission of information and innovation, and, hence, for firm performance. Using worker transitions from particularly productive firms, a number of recent studies show that mobility substantially contributes to the diffusion of human capital and helps increase productivity (Song, Almeida, and Wu, 2003; Balsvik, 2011; Parrotta and Pozzoli, 2012; Stoyanov and Zubanov, 2012; Poole, 2013; Serafinelli, ming). In particular, mobility of managers plays a crucial role for firm productivity, confirming parallel results in our paper (Mion and Opromolla, 2014; Bender, Bloom, Card, Van Reenen, and Wolter, 2016).

The paper further contributes to the literature on bunching at kinks and notches in the tax schedule started by Saez (2010) and Chetty et al. (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, 2017; Seibold, 2017).[4] We provide novel evidence on the dynamics of bunching by tracking economic agents over time. We exploit changes in the bunching estimate for workers 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).[5] We look at bunching

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

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

among wage earners in a development setting and find strong reactions to a very small kink.[6]

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 use 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 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 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.

Finally, we contribute 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, 2017). 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.

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.[7] In the past years the government has implemented a range of economic and political reforms

[6]The first kink (income tax exemption threshold) 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. In line with the literature on the role of deduction opportunities in personal income taxation (Doerrenberg, Peichl, and Siegloch, 2017; Matikka, ming), strong bunching responses at this first kink are driven by reporting effects using deductions and not real labor supply responses.

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

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. 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. 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), corporate taxes (22% of profits since 2013), a tax on foreign money transfers, and special consumption taxes. One of the main reasons for higher tax revenue is an increase in formalization of the economy induced by the tax administration's wide-ranging efforts to increase tax compliance.

The most relevant policy is the introduction of extensive deduction possibilities in income tax, substantially increasing the demand for formal receipts.[8] 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. From a firm's perspective, 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.

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. Between 2006 and 2015, the total number of tax declarations submitted 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.[9] Tax liability in Ecuador is individually determined (i.e., no family taxation).[10] The PIT liability is calculated progressively with numerous small jumps in the marginal tax rate, starting at 5% and going up to 35%. The cutoff income levels change yearly according to inflation.[11]

[8] Sellers of goods and services are obliged to offer two different types of receipts. The standard receipt ("nota de venta") includes information on goods and prices, while the enhanced version ("factura") contains additional information about the client's name and unique identification number. Only these detailed receipts issued to the taxpayer or his/her dependents can be presented to the tax authority. This policy guarantees a paper trail and impedes illegal sale of receipts. Further policies to increase tax compliance include improved information sharing between government agencies.

[9] 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.

[10] 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.

[11] The rate used for inflation adjustments is the yearly change in consumer price index for urban areas published by Ecuador's National Statistics Institute INEC on November 30 of a given year. Exact nominal values since 2006 are displayed in Table A.1 in the appendix. In 2008, the government enacted

PIT in Ecuador starts being levied only at relatively high levels. In 2013, the exemption threshold was set such that income tax was not charged on annual income below 10,180 USD.[12] 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). Therefore, PIT is only applicable to individuals in the top 10 % of the distribution of formal sector income.

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 × 10,180 = 13,234 USD).[13] 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 USD, in 2013[14]), 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. PIT is primarily filed on a firm-reported tax form (F107, see figure A.1 in the Appendix). This form can only be submitted to the tax authority by the employer 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 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, individuals can also use it to update the employer-reported information.

a series of tax system reforms, including increasing the top marginal tax rate from 25% to 35%.

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

[13] 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.

[14] Until 2010 this limit was set at 7500 USD.

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 PIT returns of regular employees (tax form F107) for the years 2006-2015.

We augment these tax records by three additional 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*). 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.[15] We end up with detailed matched employer-employee data that allows us to track taxpayers, firms, and co-workers over time.

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 yearly individual 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 (cf. footnote 11). 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. About one quarter of the formal sector employees are in the public sector.[16]

Figure 1 displays the reported income distribution 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 USD and plotted as bin frequencies for each bin. In general, the distri-

[15] Firms are obliged to file a corporate tax declaration if their annual gross income exceeds 100,000 USD. 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.

[16] We exclude public 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.

bution of gross income in the upper panel 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 smooth around all kink points of the marginal tax schedule depicted in the figure. The distribution of *taxable* income (gross income minus any deductions) in the lower panel, however, looks different. There is a pronounced spike in the distribution just before the exemption threshold. The difference between gross and taxable income indicates that tax avoidance is driven by reporting effects rather than real labor supply responses.

Our main measure of tax avoidance is the amount of individuals adjusting their income such that they locate just below the tax exemption threshold ("bunching"). In online Appendix C, we conduct our entire analyses using two alternative measures of tax avoidance, the amount of individuals reducing their taxable income to any value below the first kink and the amount of individuals with deductions with very similar results.

While bunching is strong at the exemption threshold, we do not observe any bunching at subsequent kink points of the marginal tax schedule. 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.

The relevance of dynamic aspects in driving tax adjustment behavior becomes especially pronounced when tracking the number of taxpayers over time. Figure 2 indicates a strong 2.5-fold increase in the number of private sector employees with tax-liable gross income between 2006 and 2015 (blue triangles).[17] After the introduction of generous deduction possibilities in 2008, however, a substantial and increasing share of employees reduced their reported taxable income below the exemption threshold (red dots). The growing wedge between gross income and taxable income results in a decreasing share of individuals that actually pay taxes (green squares on right hand axis) and reflects the growth in tax avoidance over time. The main part of our analysis examines the learning processes driving this dynamic increase in tax avoidance.

[17] 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.

4 Results

In this section we present empirical results from our analysis of learning dynamics about avoidance opportunities in personal income taxes. The first part 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 documents firm-level dynamics in tax adjustment behavior and identifies peers and experts as the main drivers of information transmission on tax avoidance opportunities. Throughout this section, our measure of tax avoidance is bunching just below the income tax exemption threshold. All of our results, however, are robust to using two alternative measures for tax avoidance: reducing taxable income to any value below the exemption threshold and an indicator for using deductions. Please refer to online Appendix C for all graphs and tables using these alternative definitions.

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 USD bin size) and leaving out a window around the kink (1000 USD to the left and 50 USD to the right), 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.[18] Figure 3 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.[19]

4.1 Individual Dynamics

In this section we explore the dynamics in the usage of tax adjustment opportunities among individual workers. First, we document strong increases in tax avoidance as individuals gain experience in the formal sector. Second, we provide causal evidence for the influence of the firm information environment on individual learning processes.

[18]Standard errors are obtained using a non-parametric bootstrap procedure. Our results are robust to 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 (available on request).

[19]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 (see also Blomquist and Newey (2017)). 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).

4.1.1 Individual Learning

The massive expansion in the number of taxpayers in Ecuador allows us to follow cohorts of individuals who entered the formal sector at various points in time. Hence, we compare bunching levels among the same set of individuals depending on their tenure in the formal system. To hold the sample composition constant within cohorts, we restrict the sample to individuals that are observed without interruption once they entered the formal economy.

Table 1 displays bunching estimates over time for different cohorts. 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. 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.[20] Bunching in gross income (Panel B of Table 1), in contrast, stays relatively low and does not increase as individuals gain experience in the formal system.

One major concern in comparing bunching estimates according to tenure and experience in the formal system is that workers might sort into firm environments where it is more common to bunch. Hence, 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 regress an indicator whether a worker bunches on flexible functions of experience in the formal sector while controlling for a broad range of observable characteristics and unobserved heterogeneity.[21] Table 2 presents results from various specifications of a simple linear probability model. The first three columns show regression results for a linear, quadratic, and cubic polynomial in years of experience. In all specifications, we include year fixed effects to control for general time trends. The estimates show strong initial increases in the probability to bunch which level off after 4

[20] 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.

[21] We define bunching as having taxable income within the range of 1000 USD to the left of the exemption threshold and restrict the sample to individuals in the years 2006-2015 with gross income above the exemption threshold but still within the relevant range for bunching using the deduction possibilities.

to 5 years. In Column (4), we add individual-level control variables such as an age polynomial, gender, education, marital status, nationality and the number of jobs a worker holds in the given year, but do not observe any change in the impact of experience on bunching. Women and married individuals are more likely to bunch and tax avoidance increases with age. Higher education levels tend to increase the likelihood of bunching. Having multiple jobs within a year makes it more difficult to adjust income and deductions and therefore reduces the probability of bunching. In order to take care of income dynamics as potential confounders, Column (5) additionally controls for (log) gross income and income growth. The coefficients on experience are slightly smaller in magnitude but still strongly significant and indicate the same pattern of diminishing effects as in previous specifications. In Column (6) we add firm-level characteristics such as firm age, firm size, an indicator for corporate firm status, and industry (14 broad categories) and region (24 provinces) fixed effects with no change in the main effects. The identifying variation hence derives from differences in experience within industry and within region cells, holding fixed observable characteristics and general time trends. Finally, incorporating worker fixed effects in Columns (7) indicates that the relation between experience and bunching behavior remains stable when the effects are identified by within-individual variation in experience.

Overall, the learning process can be described well by a 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 probability of 3 to 6 percentage points. The increase becomes less steep over time and levels off completely after four to five years of experience. The development of the effects is clearly presented in Figure 4 which displays coefficients in a specification that controls for worker fixed effects as Column (7) but includes separate dummy variables for each year of experience in the formal sector.[22]

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 – even when controlling for income dynamics and other potential confounding factors. 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

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

[22]The estimates are interpreted relative to the first year in the formal sector (with no previous experience).

workers moving into a high-avoidance environment to those moving into a low-avoidance environment. In contrast to that paper, however, we examine job-to-job transitions between firms directly (instead of regional mobility). Due to several identification strategies addressing possible strategic job mobility patterns, we are able to make statements about the causal effect of information environments on individual tax avoidance behavior.

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[23] and only an individual's first job transition.[24] 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 co-workers who are bunching.[25] Table 3 reports summary statistics for our sample of job switchers. We concentrate on workers who work in the medium quintile and move to the bottom, medium, or high quintile. Average characteristics of these workers are displayed in Column (1). Demographic characteristics as well as income before and after the job transition differ substantially between workers with different destination quintiles. Column (2) reports characteristics for switchers to the bottom quintile and Column (3) indicates significant differences to workers who switch to another firm in the medium quintile. Similarly, Columns (5) reports characteristics for those switching to the high quintile and Column (6) provides significant differences to those switching to the mid quintile. We therefore employ a broad range of identification strategies that address the potential selection of workers into specific knowledge environments. The main challenge is that transitions into higher knowledge quintiles are also associated with higher wage increases. We first provide graphical evidence of bunching shares around the job transition based on raw data before we address selection using event study regressions with (1) a broad range of control variables including wage growth and unobservable worker heterogeneity, (2) a matched control group with excellent balancing properties, and (3) the subsample of workers who switch their job due to exogenous job displacement.

Graphical Evidence Using an event study graph, we observe the dynamic adjustment process of individuals depending on the quintile they are moving towards. Figure 5 plots the share of bunchers among workers starting from a firm in the mid-quintile of the

[23]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.

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

[25]For every year, we compute the distribution of the share of co-workers who bunch and split the sample into quintiles. As before, we define bunching as reporting taxable income of 1000 USD 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.

bunching distribution. The horizontal axis indicates the year relative to the move with year zero being the first year at the destination firm. The data show an 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 5 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 dynamics between these groups of taxpayers. To address potential selection effects, we employ a range of identification strategies that control for unobserved heterogeneity and observed characteristics such as earnings and wage growth before and after the job switch.

Controlling for observed and unobserved heterogeneity In our first strategy, we estimate several regression-based versions of the event study design that control for a broad range of observable worker and firm characteristics and allow for unobserved heterogeneity across workers by incorporating individual worker fixed effects. Hence, the effect of the job switch on bunching is identified by the time variation within individuals. We run the following regression on the subsample of individuals starting in the medium quintile of the bunching distribution:

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

The dependent variable Y_{it} measures tax avoidance as an indicator for individual i having taxable income within a 1000 USD window to the left of the exemption threshold in year 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-avoidance firm. We control for time-varying individual and firm characteristics X_{it} including gross income, wage growth, age squared, firm size, industry classification (18 broad industries), firm location (24 provinces), and corporate firm status. Last, we account for various sources of unobserved heterogeneity by including individual fixed effects (α_i), year fixed effects (λ_t) and fixed effects in event time (γ_k). We run a parallel analysis for individuals switching from a firm in the mid to the low quintile with $quintile_i$

[26] Table B.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.

being an indicator for the low quintile.

The estimates are displayed in Panel A of Table 4. Columns (1) and (5) are without and columns (2) and (6) 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 about 3 percentage points while moving to the low quintile has no significant effect.[27]

Explicitly looking at the timing of the effects, 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 separately for each year reported in Panel B of Table 4.[28] We find no evidence of anticipatory effects before the event. Switching into a high quintile firm leads to a persistent increase in bunching strongest in the second year after the move. In contrast, job transitions to a low avoidance environment are not associated with significant effects.

In a 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. Specifically, we estimate

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

with the variables as defined above.[29] Our coefficients of interest γ_k are reported in Panel C of Table 4. We find very similar results to before, emphasizing the robustness of our findings.

Matched control group In a second identification strategy, we define the comparison group for movers into a low and high knowledge environment by matching workers from the mid to mid group based on similar propensities to switch to the same environment. The matching algorithm is based on exact matches with regard to the industry and region in the period before the job switch and estimates propensity scores by a probit regression controlling for age, marital status, gender, education, and gross income in the years before and after the job transition. For each worker with a destination firm in the high (or low)

[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 results.

[28] As is standard in the literature, we compare all effects to the year before the event.

[29] 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.

quintile, we then select the comparison worker with the closest propensity score among those switching to a firm in the medium quintile. Columns (4) and (7) of Table 3 show that worker characteristics are now nicely balanced between the groups of analysis, even for characteristics that were not part of the matching algorithm, such as taxable income and bunching status in the pre-switch period.

Columns (3) and (7) of Table 4 indicate that estimating equations (1) and (2) on the matched sample does not change the results. While moving to a low-bunching environment still does not result in a reduction of bunching, the point estimates for moving to a high-bunching environment are remarkable stable. Exposure to a high-bunching firm still leads to significant increases in tax avoidance by about 3 percentage points.

Sample of displaced workers In our final identification strategy, we rule out strategic job mobility by restricting the sample to the subset of workers that switch their job due to a firm closure. In the spirit of Jacobson, LaLonde, and Sullivan (1993), this extracts the exogenous part of job mobility through job displacement. The event study graph in the sample of displaced workers (with a remaining 23,988 job transitions) is shown in Figure 6. It looks very similar to the full sample of job switchers. Intuitively, however, the effect is slightly delayed since displaced workers need longer to find new employment. Columns (4) and (8) of Table 4 report results for the same regressions as in the full sample of job switchers. Despite the much smaller sample size, results for the subsample of exogenously displaced workers are remarkably similar to the full sample, indicating that strategic mobility to specific bunching environments does not play a major role.

Our results provide robust 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). The firm environment is crucial in driving individual learning on bunching opportunities. Consistent results using various different identification strategies lead us to the conclusion that there is a causal relationship between the firm-level knowledge environment and individual tax avoidance. In the following section, we therefore examine dynamic learning processes on the firm level.

4.2 Firm Dynamics

The importance of the firm environment for individual tax avoidance behavior as well as the institutional setting in which firms directly submit tax declarations on behalf of their employees motivate a detailed study of firm dynamics. We document a strong increase in the likelihood to have bunchers in the workforce as firms gain experience in the formal sector (Section 4.2.1). Moreover, we identify two key mechanisms of information transmission between and within firms: peers and experts (Section 4.2.2).

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 impact of the availability of information on tax avoidance at the firm level.

We measure firm-level information on tax adjustment opportunities by looking at the 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 5 reports the share of firms with at least one buncher among the potential bunchers for each year and cohort. 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 6 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 lies between 25 and 35 %. Notably, this share does not increase considerably with experience.

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. Given that a firm has taken the decision to allow for bunching, a relatively stable fraction of workers (around 30 percent) makes use of tax avoidance opportunities. In order to gain a more detailed understanding into what drives these firm-level decisions to start bunching, the following section analyzes how information spreads between and within firms.

4.2.2 Channels of Information Transmission

In this section, we characterize the channels of information transmission underlying the information flows between workers and firms. We focus on two specific channels we

[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.

can identify in the data: Peers and experts. The peers channel, specifically information transmission from new co-workers towards incumbent workers, represents an important aspect of changes in the information environment at a given firm. We hypothesize that co-workers who were bunching in their previous firm induce their new colleagues to engage in bunching themselves. The experts channel focuses on the role of accountants. Here we hypothesize that accountants previously working for a firm with bunching activity might bring knowledge about tax avoidance opportunities to their new firm. We identify the effect of these channels through changes in the co-worker environment and accountant switches. Moreover, we shed light on the anatomy of information flows within a firm by differentiating incoming co-workers according to their relative position within their destination firm's distribution of wages.

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 tax declarations and thereby an identifier for the accountant.[32] We quantify the effect of the information transmission channels by estimating various linear probability models where we regress our measure of tax avoidance at the firm level on indicators whether the firm employs knowledgeable co-workers and/or accountants. In particular, we estimate variants of the following regression equation:

$$\begin{aligned} Y_{jt} = \beta_0 &+ \beta_1 \textit{co-worker bunch}_{jt} + \beta_2 \textit{co-worker bunch} \times \textit{above}\, p90_{jt} \\ &+ \beta_3 \textit{accountant bunch}_{jt} + \gamma X_{jt} + \alpha_j + \lambda_t + \epsilon_{jt} \end{aligned} \tag{4}$$

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 variable $\textit{co-worker bunch}_{jt}$ is an indicator for a firm having an employee who was bunching at the previous employer.[33] The incoming buncher variable is interacted with an indicator, $\textit{above}\, p90_{jt}$, that is equal to one in case the incoming worker earns a wage in the 90th percentile of the destination firm's wages distribution. The indicator variable $\textit{accountant bunch}_{jt}$ 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.[34]

Throughout these regressions, we include year fixed effects (λ_t) and control for a range

[32] About one fifth of the firms used in this panel do not need to file corporate tax declarations and thereby do not have official accountants. These are generally smaller firms for which it would in any case be more difficult to have enough variation to identify the channels of information transmission.

[33] We only consider incoming co-workers who were bunching in the year before joining their current firm and had gross income in the range for potential bunchers. Moreover, the $\textit{co-worker bunch}_{jt}$ indicator is equal to one in all periods in which this incoming buncher remains at the destination firm.

[34] 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 terms of his knowledge about bunching.

of time-varying firm level variables 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 gross 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 7 reports the results on the information transmission channels. Columns (1) through (3) quantify the effects of information transmission through peers and columns (4) and (5) consider information transmission through accountants. The remaining five columns represent the same specifications, but additionally include firm fixed effects (α_j), thereby controlling for unobserved firm-level heterogeneity. In these specifications the identifying variation derives from *changes* in the peer composition and *switches* in the accountants of a given firm.

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 about 9 percentage points. 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. Most of this effect is driven by employees taking up jobs relatively high in the destination firm's wage distribution. When including an indicator for incoming bunchers above the 90th percentile, the overall effect of incoming bunchers is strongly diminished and becomes insignificant, but the interaction with high-wage earning incomers is strong and significant. Bunchers joining their new firm between the 50th and the 90th percentile also have a positive impact on their coworker's bunching behavior, however, this effect is weaker than for incoming bunchers in the 90th percentile. This lets us conclude that the spread of information within a firm can be characterized through a "top-down" learning process.

Top-down learning also determines the effects of the experts in charge of accounting at a firm. Periods in which a firm has a knowledgeable accountant are associated with increases in bunching of about 5.4 percentage points, which corresponds to an increase in firm-level bunching by about 13 percent. The effects remain virtually unchanged when including both types of knowledge flows (peers and experts) simultaneously in columns (5) and (10) indicating that these are two separate mechanisms.

In order to get a grasp of what types of firms help their employees bunch, we draw on our rich firm-registry data to characterize bunching firms according to observables. The first five columns of Table 7 show the effects of time-varying and time-invariant observables at the firm level on bunching behavior. Firms with younger and more female workers are more likely to engage in bunching. Larger firms' employees are also more likely to bunch. Industry 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.

Table 8 shows results from a similar set of 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 behavior.[35] Especially in our robust specifications including firm fixed effects, almost all of our estimates of the channels are very small and insignificant. 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.

To summarize, peers and experts 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. Moreover, anatomy of information flows within firms shows that information is passed by managers and accountants in a "top-down" manner.

Peers This section causally identifies the peers channel by looking at individuals with recent changes to their co-worker composition. We compare a treatment group of firms with incoming bunchers to a suitable control group and analyze how knowledgeable co-workers affect the behavior at their new firm. We find strong spillover effects of new co-workers on the probability that incumbent co-workers will bunch.

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. 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")[36] 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 9 provides descriptive statistics for the workers in this sample of firms. Along key demographic variables, the full sample (all firms receiving incoming co-workers) is very similar to the treated group. However, as shown in Column (3), there are significant differences between the treatment and control group in terms of gross and taxable income

[35] Akin to the sample restrictions in Table 6, we focus on firms with at least 5 potential bunchers in order to abstract from very small firms with high variability in bunching shares conditional on bunching.

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

both before and after the incoming event. To account for these differences, we create a matched control group, to which the differences disappear (Column 4).[37]

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 co-worker. 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 co-worker and focuses only on the employees already working at a given firm. The results in Figure 7 suggest that incoming workers have a strong effect on the tax adjustment behavior of their co-workers. Firms in the treatment group are much more likely to have bunchers among their incumbent employees after receiving a new co-worker.

Table 10 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 there is bunching activity among incumbent workers, $post_{jt}$ 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 firm-level characteristics (firmsize, average gross income, corporate status, and industry and province dummies) as well as employee characteristics (average income, share tertiary educated, average age, share married, and share female).

The results are displayed in Panel A of Table 10. Parallel to the analysis in Section 4.1.2, we examine effects separately for each year relative to the job transition in Panel B. Even when controlling for unobserved heterogeneity and a rich set of observables, the peer learning channel is strong and pronounced (Column 2). Moreover, when using the matched control group, we find even stronger effects (Column 3). An incoming buncher increases the probability that at least one of the incumbent co-workers bunches by about 5 to 7 percent. The effects are strongest in the second year after the incoming event, consistent with the idea that it takes some time for incoming co-workers to spread the information to the new firm environment.[38] In the appendix we conduct a heterogeneity

[37] The matching algorithm employed here is a mirrored version of the one employed in Section 4.1.2 but at the firm level. The algorithm uses exact matches regarding industry by region cells in the year before the event and estimates propensity scores for being in the treatment group based on the non-outcome variables average age, share married, share female, share tertiary educated, firmsize, corporate status of the firm and average gross income pre and post event. Balance is excellent.

[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.

analysis by firm size. Figure B.4 depicts the same event study separately for small, medium and large firms. Intuitively, we find the effect of co-workers on their peers to be largest for small firms and to become smaller for larger firms.

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 causal evidence for the effect of accountants on firm-level bunching behavior.

We assess whether firm-level bunching behavior changes after firms receive new accountants. Like a new co-worker, a new accountant changes the information environment at a firm. Firms that receive a knowledgeable accountant who was previously working at a firm with bunchers constitute the treatment group. Firms in the control group also receive 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 extract the universe of accountant switches observed in the corporate tax declarations. We then analyze how accountant switches have an impact on whether a firm engages in bunching activity.[39] Table 11 shows descriptive statistics for the firms in the experts event study. Treatment and control firms are similar along key demographic variables but show significant differences in income variables before and after the accountant switch. Using our matched algorithm, however, we achieve nearly perfect balance.[40]

Figure 8 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 relative to the year of the incoming accountant (year 0). We observe stable pre-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 harder to distinguish.

Table 12 denotes regression results from event-study type regressions analogous to those in the previous section. 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. Switching towards a knowledgeable accountant is

[39]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 16,389 accountant switches.

[40]The matching algorithm in the experts event study is exactly like in the peer learning event study: exact matching on industry and region cells, with ensuing propensity score matching using average age, share married, share female, share tertiary educated, firmsize, and average gross income pre and post event.

clearly associated to a strong increase in the amount of bunching at a firm. Receiving a knowledgeable accountant increases firm-level bunching by about 2.5 percent, even when including extensive control variables and using the matched control group.

5 Conclusion

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. Tax avoidance is driven through reporting behavior based on generous deduction possibilities. By exploiting matched employer-employee data and a research design based on exogenous job mobility we find the firm information environment to have a causal effect on 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 tax avoidance behavior. We show that the knowledge environment at the firm-level can be characterized by a binary pattern: either a firm has knowledge about bunching opportunities or it does not. Conditional on tax avoidance at the firm level, the share of employees avoiding taxes remains relatively stable over time. The paper identifies and quantifies two specific channels of information transmission that explain the rise in firm-level knowledge on tax avoidance activity. We quantify the effects of peers and experts by exploiting changes in the co-worker composition of firms and accountant switches. Furthermore, we provide evidence for "top-down" information flows within firms.

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. A flexible labor market with worker and job mobility is crucial for the spread of information and helps to reduce information frictions.

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 the channels of information transmission underlying learning processes can be informative for the design of optimal policies and to guide policymakers in improving existing ones.

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Table 1: Bunching estimates over time by cohort

Cohort	2007	2008	2009	2010	2011	2012	2013	2014	2015	Observations
A. 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)	
B. 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. Sample restricted to individuals observed without interruption after entering the formal economy. The estimates are based on binned income data (50$ bin size) and a counterfactual density using a polynomial of degree 5. Bootstrapped standard errors reported in parentheses.

Table 2: Bunching Individuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience	0.0066	0.040	0.085	0.088	0.065	0.064	0.048
	(0.00058)	(0.0012)	(0.0030)	(0.0031)	(0.0063)	(0.0062)	(0.0065)
Experience^2		-0.0038	-0.015	-0.016	-0.012	-0.012	-0.0077
		(0.00012)	(0.00078)	(0.00079)	(0.0013)	(0.0013)	(0.0014)
Experience^3			0.00083	0.00089	0.00065	0.00062	0.00041
			(0.000056)	(0.000056)	(0.000083)	(0.000081)	(0.000089)
Married				0.0055	0.0038	0.0025	
				(0.0011)	(0.0013)	(0.0013)	
Age				0.0049	0.0033	0.0029	
				(0.00049)	(0.00061)	(0.00056)	
Age^2				-0.000043	-0.000026	-0.000028	
				(0.0000061)	(0.0000072)	(0.0000067)	
Female				0.015	0.019	0.011	
				(0.0017)	(0.0021)	(0.0019)	
Secondary Education				0.033	0.022	0.015	
				(0.014)	(0.017)	(0.017)	
Tertiary Education				0.032	0.015	0.0042	
				(0.015)	(0.017)	(0.017)	
Foreign				-0.0040	-0.011	-0.015	
				(0.0047)	(0.0059)	(0.0053)	
Number of Jobs				-0.043	-0.046	-0.046	-0.027
				(0.0013)	(0.0015)	(0.0014)	(0.0014)
Log Gross Income					0.032	0.038	0.060
					(0.0033)	(0.0028)	(0.0021)
Gross Income Growth					0.0062	0.0048	-0.0016
					(0.0015)	(0.0014)	(0.0014)
Corporate Firm						-0.0077	0.011
						(0.0039)	(0.0040)
Firm Age						-0.00012	-0.00018
						(0.000097)	(0.000070)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
Worker FE	No	No	No	No	No	No	Yes
R^2	0.016	0.019	0.020	0.028	0.021	0.027	0.280
Observations	618,356	618,356	618,356	618,356	508,417	508,417	508,417

The table shows results from linear regressions 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 firmsize, firm age. Standard errors (in parentheses) are clustered at the firm level.

Table 3: Job Switchers - Descriptives

	Descriptive Statistics						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	From Mid	Mid to Low	Diff	Matched Diff	Mid to High	Diff	Matched Diff
Demographics							
Age	31.75	33.27	2.00	-0.03	30.75	-0.52	0.14
	(8.84)	(9.57)	(0.16)	(0.18)	(8.16)	(0.15)	(0.15)
Married	0.46	0.47	0.02	-0.01	0.46	0.01	-0.01
	(0.50)	(0.50)	(0.01)	(0.01)	(0.50)	(0.01)	(0.01)
Female	0.29	0.30	0.03	-0.00	0.31	0.03	0.01
	(0.46)	(0.46)	(0.01)	(0.01)	(0.46)	(0.01)	(0.01)
Tertiary Education	0.23	0.23	0.02	-0.02	0.27	0.07	0.00
	(0.42)	(0.42)	(0.01)	(0.01)	(0.45)	(0.01)	(0.01)
Pre-Switch							
Gross Income	6278.08	5868.99	-409.32	140.90	6703.97	425.65	189.97
	(6305.17)	(6033.08)	(110.82)	(107.29)	(6471.90)	(115.69)	(120.25)
Taxable Income	5849.38	5493.57	-345.23	144.32	6232.53	393.73	199.15
	(5272.79)	(5083.61)	(92.94)	(89.49)	(5378.45)	(96.42)	(99.59)
Share Deduction Filers	0.08	0.07	-0.00	0.00	0.08	0.01	0.01
	(0.26)	(0.25)	(0.00)	(0.00)	(0.28)	(0.00)	(0.01)
Buncher	0.03	0.02	0.00	0.00	0.04	0.01	0.00
	(0.16)	(0.15)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)
Post-Switch							
Gross Income	6544.62	5115.60	-1921.69	-110.45	7450.82	413.52	171.57
	(6145.82)	(4953.44)	(109.62)	(87.80)	(5871.09)	(117.66)	(115.47)
Taxable Income	6039.29	4854.24	-1629.36	-104.66	6748.53	264.93	84.80
	(5064.40)	(4204.85)	(91.68)	(74.37)	(4656.59)	(96.13)	(91.92)
Share Deduction Filers	0.10	0.06	-0.04	0.00	0.14	0.05	0.04
	(0.30)	(0.23)	(0.00)	(0.00)	(0.35)	(0.01)	(0.01)
Buncher	0.04	0.02	-0.01	0.00	0.06	0.02	0.03
	(0.20)	(0.16)	(0.00)	(0.00)	(0.24)	(0.00)	(0.00)
Observations	18,318	5,919			5,682	.	.

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 co-worker 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 4: Job Switchers

	Mid to Low				Mid to High			
	(1) Full Sample	(2) Full Sample	(3) Matching	(4) Displaced	(5) Full Sample	(6) Full Sample	(7) Matching	(8) Displaced
A. Overall Effect								
After event year	-0.007	0.001	0.010	-0.002	0.034	0.028	0.028	0.025
	(0.004)	(0.004)	(0.006)	(0.014)	(0.005)	(0.005)	(0.007)	(0.018)
B. Effects by Relative Year								
Anticipatory Effects								
Event year - 3	-0.006	-0.009	-0.012	-0.007	-0.003	-0.001	0.002	0.025
	(0.007)	(0.007)	(0.009)	(0.020)	(0.008)	(0.007)	(0.011)	(0.031)
Event year - 2	-0.002	-0.005	-0.019	-0.001	0.000	0.002	0.008	0.025
	(0.005)	(0.005)	(0.009)	(0.014)	(0.006)	(0.006)	(0.010)	(0.019)
Post Treatment Effects								
Event year	-0.013	-0.006	0.003	-0.008	0.013	0.010	0.021	-0.002
	(0.005)	(0.005)	(0.006)	(0.016)	(0.006)	(0.006)	(0.008)	(0.018)
Event year + 1	-0.007	-0.000	0.002	-0.009	0.049	0.043	0.039	0.058
	(0.006)	(0.006)	(0.009)	(0.019)	(0.007)	(0.007)	(0.011)	(0.026)
Event year + 2	-0.004	0.000	-0.000	0.009	0.044	0.037	0.036	0.069
	(0.008)	(0.008)	(0.011)	(0.025)	(0.010)	(0.010)	(0.013)	(0.035)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	60,040	60,040	53,686	6,211	59,367	59,367	52,215	4,999
C. Timing								
Event year - 2	0.005	-0.002		-0.010	0.006	0.001		-0.006
	(0.004)	(0.004)		(0.017)	(0.004)	(0.004)		(0.045)
Event year	-0.000	0.005		0.012	0.026	0.022		0.059
	(0.003)	(0.005)		(0.013)	(0.005)	(0.007)		(0.040)
Event year + 1	0.015	0.016		0.030	0.071	0.059		0.151
	(0.004)	(0.008)		(0.025)	(0.006)	(0.011)		(0.077)
Controls	No	Yes		Yes	No	Yes		Yes
Observations	25,048	25,048		2,403	23,947	23,947		1,479

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.

Table 5: 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 the firm's year of entry into the formal sector. Further conditioned on employing potential bunchers in all subsequent years. Standard deviations given in parentheses.

Table 6: 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 the firm's 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 at least one buncher leads to yearly changing compositions of the cohort. Standard deviations given in parentheses.

Table 7: Information Transmission: Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Buncher	0.095	0.052	0.0051		0.050	0.089	0.040	0.029		0.041
	(0.013)	(0.019)	(0.025)		(0.019)	(0.024)	(0.032)	(0.040)		(0.032)
Incoming Buncher above p90		0.084	0.12		0.082		0.11	0.12		0.11
		(0.024)	(0.028)		(0.024)		(0.043)	(0.048)		(0.043)
Incoming Buncher between p50 and p90			0.088					0.023		
			(0.029)					(0.055)		
Knowledgeable Accountant				0.054	0.053				0.054	0.054
				(0.0060)	(0.0060)				(0.0096)	(0.0096)
Avg. Age	-0.0021	-0.0021	-0.0021	-0.0021	-0.0020	-0.0031	-0.0030	-0.0030	-0.0031	-0.0030
	(0.00054)	(0.00054)	(0.00054)	(0.00054)	(0.00054)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Share Female	0.027	0.027	0.027	0.028	0.028	-0.048	-0.047	-0.047	-0.050	-0.046
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Between 25 and 250 Employees	0.071	0.072	0.071	0.079	0.073	0.078	0.079	0.079	0.080	0.079
	(0.0067)	(0.0067)	(0.0067)	(0.0066)	(0.0066)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
More than 250 Employees	0.20	0.19	0.19	0.22	0.19	0.26	0.25	0.25	0.27	0.26
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Manufacturing	0.046	0.045	0.045	0.048	0.044					
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)					
Construction	0.037	0.037	0.037	0.038	0.037					
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)					
Trade; Repairing	0.055	0.055	0.055	0.056	0.055					
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)					
Hotel and Restaurant	0.042	0.041	0.042	0.039	0.038					
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)					
Transport, Storage, Communication	0.032	0.032	0.032	0.036	0.033					
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)					
Financial Sector	0.081	0.081	0.081	0.085	0.084					
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)					
Real Estate, Business and Renting	0.047	0.047	0.047	0.047	0.046					
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)					
Education	0.036	0.036	0.036	0.037	0.037					
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)					
Health and Social Services	0.032	0.030	0.031	0.033	0.031					
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)					
Other	0.040	0.040	0.040	0.043	0.041					
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	35025	35025	35025	35025	35025	35025	35025	35025	35025	35025

Note: The outcome variable is a binary indicator for a firm having at least one buncher. Further unreported controls: share married, share with tertiary education, average gross income, lagged bunching behavior, as well as year and province fixed effects. Standard errors clustered at firm level.

Table 8: Information Transmission: Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Buncher	-0.027	-0.011	-0.0042		-0.011	-0.018	-0.013	0.0052		-0.013
	(0.0085)	(0.013)	(0.016)		(0.013)	(0.012)	(0.017)	(0.021)		(0.017)
Incoming Buncher above p90		-0.029	-0.035		-0.030		-0.010	-0.025		-0.010
		(0.015)	(0.017)		(0.015)		(0.023)	(0.025)		(0.023)
Incoming Buncher between p50 and p90			-0.012					-0.042		
			(0.018)					(0.022)		
Knowledgeable Accountant				0.0079	0.0089				-0.00012	0.00026
				(0.0064)	(0.0064)				(0.0089)	(0.0088)
Avg. Age	-0.0011	-0.0011	-0.0011	-0.00088	-0.0011	0.00096	0.00092	0.00084	0.0011	0.00092
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Share Female	0.063	0.063	0.063	0.065	0.063	0.042	0.041	0.042	0.046	0.041
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Between 25 and 250 Employees	-0.089	-0.089	-0.089	-0.092	-0.089	-0.011	-0.012	-0.011	-0.011	-0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
More than 250 Employees	-0.19	-0.19	-0.19	-0.20	-0.19	-0.037	-0.037	-0.036	-0.039	-0.037
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Manufacturing	-0.013	-0.013	-0.013	-0.015	-0.013					
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)					
Construction	0.013	0.013	0.013	0.012	0.013					
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)					
Trade; Repairing	0.024	0.025	0.025	0.024	0.025					
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)					
Hotel and Restaurant	0.0062	0.0069	0.0066	0.0051	0.0062					
	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)					
Transport, Storage, Communication	0.0099	0.0100	0.0098	0.0091	0.0098					
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)					
Financial Sector	0.036	0.035	0.035	0.037	0.036					
	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)					
Real Estate, Business and Renting	0.015	0.015	0.015	0.014	0.015					
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)					
Education	-0.0097	-0.010	-0.010	-0.011	-0.011					
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)					
Health and Social Services	-0.036	-0.035	-0.035	-0.037	-0.035					
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)					
Other	-0.014	-0.014	-0.014	-0.015	-0.014					
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	7264	7264	7264	7264	7264	7264	7264	7264	7264	7264

The outcome variable is the share of bunchers among potential bunchers. Further controls: lagged bunching behavior, share married, share with tertiary education, average gross income at firm, as well as year and province fixed effects. Standard errors clustered at firm level.

Table 9: Peer Learning Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.02	36.21	0.21	-0.01
	(6.03)	(5.54)	(0.35)	(0.44)
Share Married	0.52	0.53	0.01	-0.00
	(0.24)	(0.22)	(0.01)	(0.02)
Share Female	0.37	0.40	0.03	-0.02
	(0.27)	(0.27)	(0.02)	(0.02)
Share Tertiary Education	0.32	0.33	0.01	0.02
	(0.26)	(0.26)	(0.02)	(0.02)
Pre-Event				
Firmsize	50.74	51.24	0.57	1.20
	(120.13)	(108.95)	(6.90)	(7.86)
Corporate Firm	0.85	0.88	0.04	-0.01
	(0.36)	(0.32)	(0.02)	(0.02)
Avg Gross Income	6903.01	7748.11	956.12	302.87
	(4052.51)	(4918.06)	(232.12)	(383.09)
Avg Taxable Income	6231.00	6902.77	760.02	197.43
	(3177.46)	(3722.10)	(181.98)	(300.44)
Share with Bunchers	0.21	0.25	0.04	0.03
	(0.41)	(0.43)	(0.02)	(0.03)
Post-Event				
Avg Gross Income	7761.76	8330.30	643.22	338.10
	(3949.91)	(4244.95)	(226.58)	(336.69)
Avg Taxable Income	6925.06	7258.80	377.58	96.83
	(3073.59)	(3032.26)	(176.42)	(253.22)
Share with Bunchers	0.28	0.35	0.07	0.08
	(0.45)	(0.48)	(0.03)	(0.04)
Observations	2,954	343		

Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the peer learning channel. The sample consists of all firms receiving one incoming employee between 2010 and 2014 and for which it is possible to observe at least two consecutive years before and after the event. Treated refers to firms receiving incoming potential bunchers that bunched prior to joining their new firm. Column (3) displays the difference between treated and control and column (4) this same difference for the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, corporate status of firm and average gross income pre and post event. Pre-event refers to the year before the arrival of new co-workers and post-event to the first year after the arrival of the new coworkers.

Table 10: Peer Learning - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.052	0.047	0.069
	(0.022)	(0.022)	(0.029)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	0.010	0.012	0.003
	(0.024)	(0.024)	(0.033)
Post Treatment Effects			
Event year	0.035	0.031	0.039
	(0.028)	(0.028)	(0.037)
Event year + 1	0.072	0.067	0.105
	(0.031)	(0.030)	(0.040)
Event year + 2	0.065	0.061	0.063
	(0.039)	(0.039)	(0.051)
Controls	No	Yes	Yes
Observations	15,913	15,913	3,696

Notes: The table reports results from the event-study regression equation (5) at the firm level. Outcome variable is the leave-out firm bunching decision and event year refers to the year of incoming employees. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, corporate status of firm, as well as industry and province dummies and dummies for the year of the incoming event. Standard errors (in parentheses) are clustered at the firm level.

Table 11: Experts Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.00	36.03	-0.07	0.19
	(7.40)	(7.25)	(0.16)	(0.20)
Share Married	0.47	0.47	-0.01	0.01
	(0.28)	(0.27)	(0.01)	(0.01)
Share Female	0.41	0.41	0.00	-0.01
	(0.30)	(0.30)	(0.01)	(0.01)
Share Tertiary Education	0.28	0.28	-0.00	0.01
	(0.28)	(0.27)	(0.01)	(0.01)
Pre-Event				
Firmsize	43.99	53.73	13.25	9.28
	(178.40)	(248.55)	(3.91)	(5.76)
Avg Gross Income	5217.38	5932.17	894.75	-9.81
	(4529.22)	(5038.55)	(100.07)	(144.85)
Avg Taxable Income	4766.13	5316.95	683.17	-23.41
	(3671.01)	(4066.28)	(81.31)	(117.07)
Share with Bunchers	0.13	0.18	0.06	0.02
	(0.34)	(0.38)	(0.01)	(0.01)
Post-Event				
Avg Gross Income	5227.81	6026.00	1025.94	29.23
	(4668.04)	(5393.24)	(91.34)	(146.31)
Avg Taxable Income	4770.90	5370.95	773.96	6.58
	(3837.20)	(4298.05)	(75.20)	(117.86)
Share with Bunchers	0.14	0.20	0.08	0.05
	(0.35)	(0.40)	(0.01)	(0.01)
Observations	16,389	3,337		

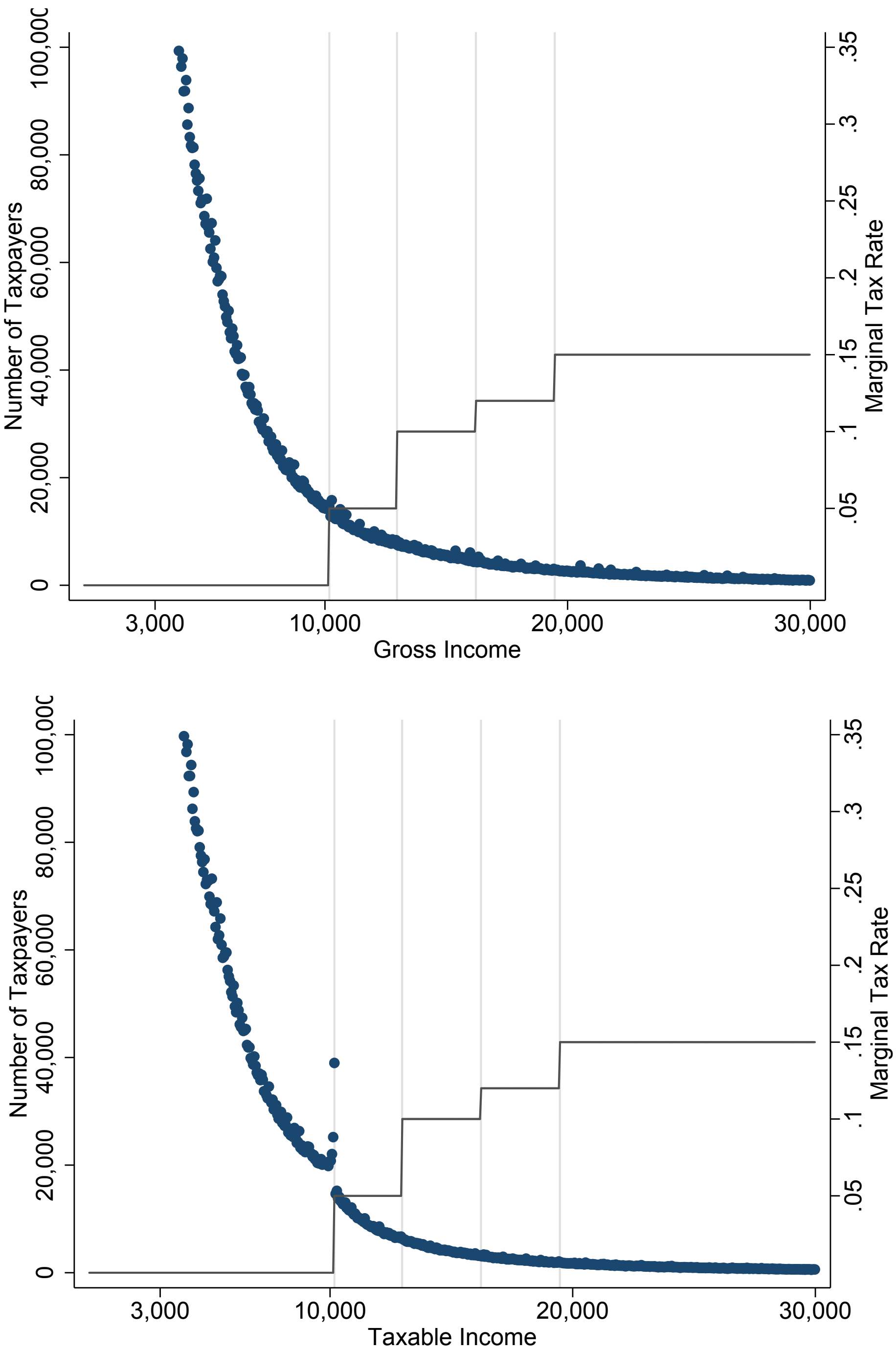
Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the experts channel. The sample is based on the universe of accountant switches between 2010 and 2014 for which it is possible to observe at least two consecutive years before and after the event and the firms employ potential bunchers throughout. Cases in which firms simultaneously received knowledgeable and non-knowledgeable accountants were excluded. Treated refers to firms receiving new accountants previously working at a firm with bunching employees. Columns (3) displays the difference to a control group consisting of firms receiving an accountant previously working at a firm with potential bunchers but with zero bunching employees. Column (4) displays the difference to the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, and average gross income pre and post event. Pre-event refers to the year before the arrival of the new accountants and post-event to the first year after the arrival of the new accountants.

Table 12: Experts Event Study - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.103	0.024	0.025
	(0.007)	(0.008)	(0.013)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	-0.018	-0.010	0.001
	(0.008)	(0.009)	(0.015)
Post Treatment Effects			
Event year	0.069	0.021	0.028
	(0.008)	(0.009)	(0.016)
Event year + 1	0.115	0.024	0.023
	(0.010)	(0.011)	(0.018)
Event year + 2	0.133	0.013	0.023
	(0.012)	(0.013)	(0.022)
Controls	No	Yes	Yes
Observations	60,483	60,483	22,485

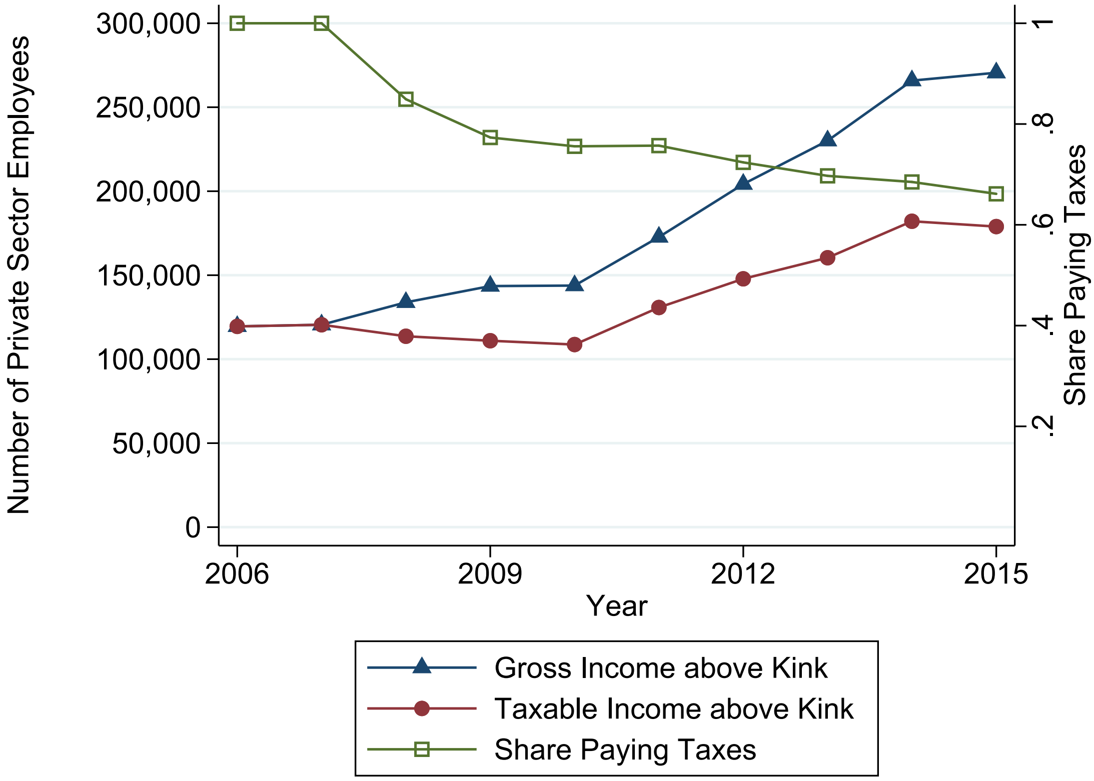
Notes: The table reports results from the event study regressions quantifying the experts channel detailed in Section (4.2.2). Outcome variable is the firm bunching decision and event year refers to the year of the incoming accountant. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, as well as industry and province dummies and dummies for the year of the accountant switch. Standard errors (in parentheses) are clustered at the firm level.

Figure 1: Income Distribution in Ecuador



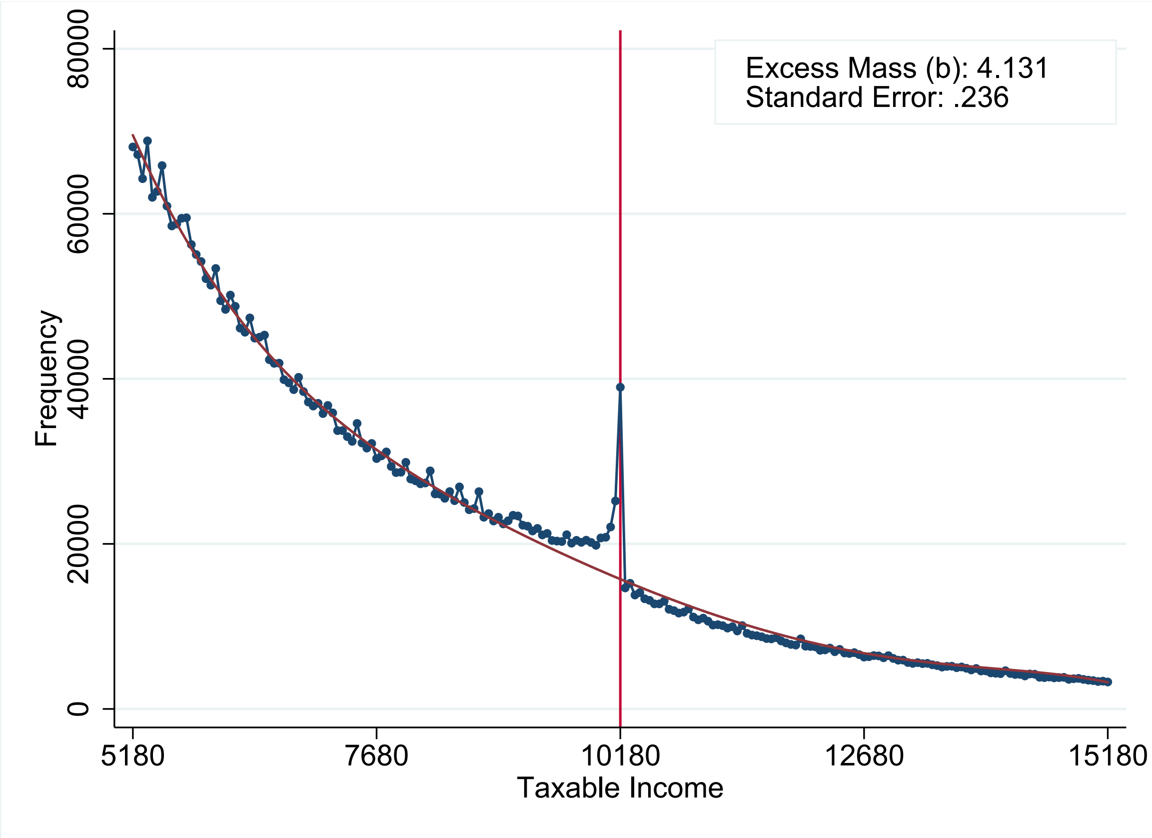
This figure shows binned scatterplots of the distribution of gross income (upper panel) and taxable income (lower panel) in Ecuador. We restrict the sample to individuals who earn at least 12 times the monthly minimum wage and at most 30,000 USD. The income distribution is contrasted with the marginal tax schedule (right y-axis) and vertical lines mark the location of kink points in the marginal tax rate.

Figure 2: Number of Employees



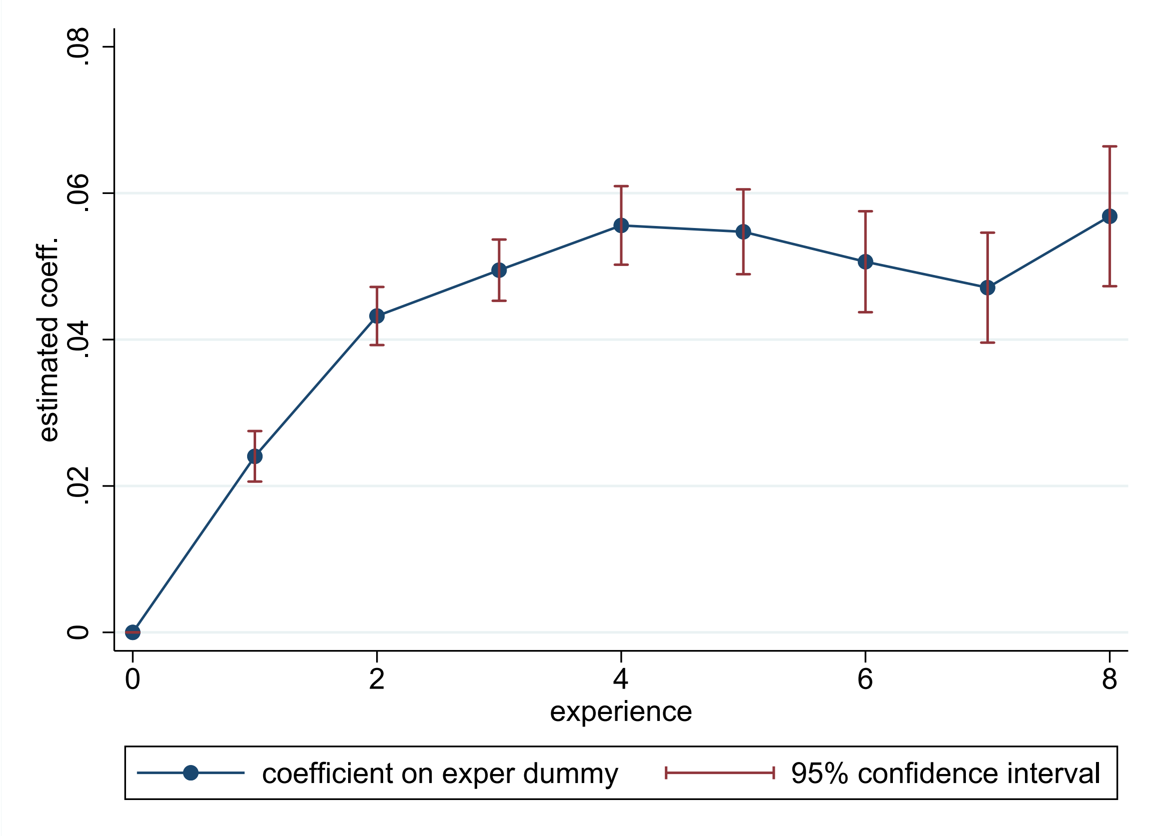
This figure displays the number of tax declaration of employees with gross and taxable income above the tax exemption threshold over time. The green squares indicate the share of individuals with taxable income above the kink among those with gross income above the kink (right y-axis).

Figure 3: Bunching Estimates Taxable Income



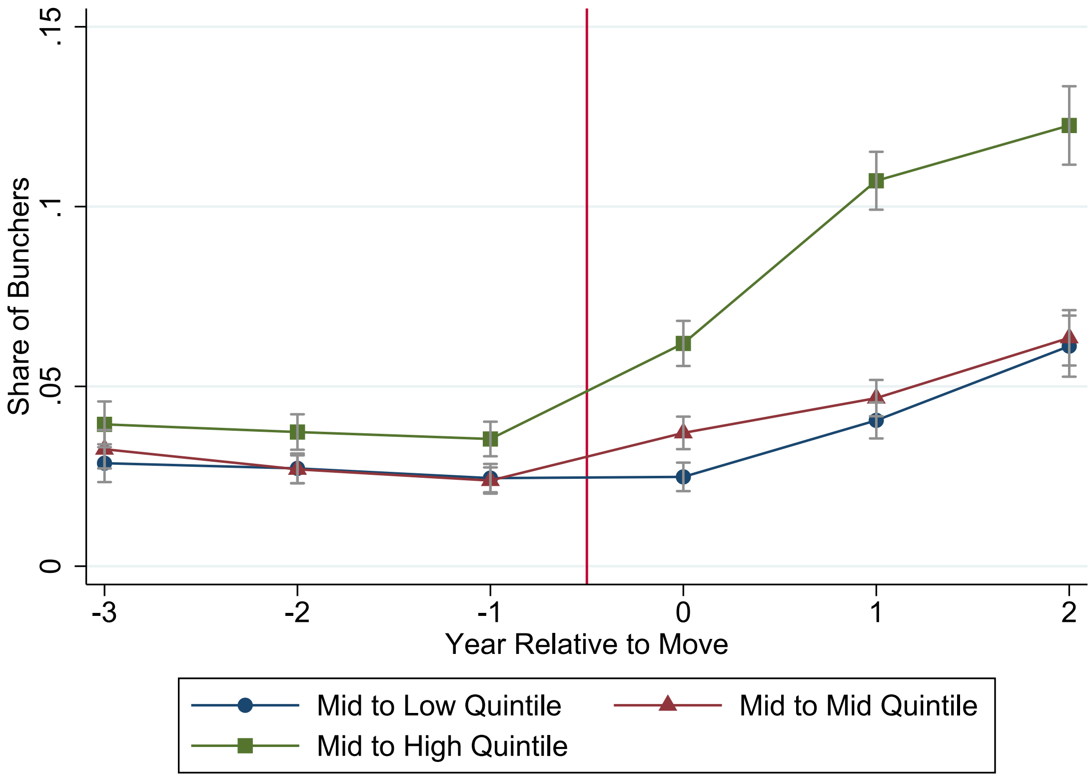
This figure shows the actual distribution of taxable income around the tax exempt threshold as a binned scatterplot with 50 USD bin width. The red line shows a polynomial fit (of degree 5) to the distribution leaving out bins in a window around the kink (1000 USD to the left and 100 USD to the right). The vertical line indicates the location of the kink point.

Figure 4: Coefficients on experience dummies



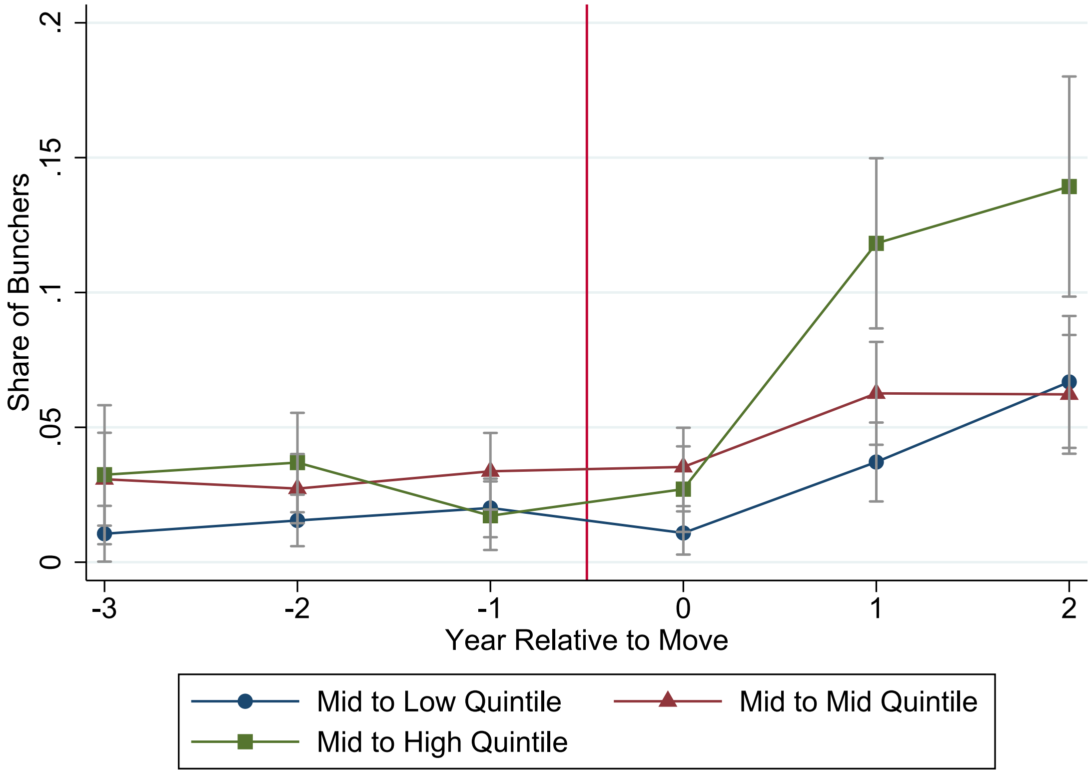
This figure depicts estimated coefficients from a linear regression of a bunching indicator on dummy variables for each year of experience in the formal sector. We control for individual fixed effects, income dynamics and a broad range of firm characteristics.

Figure 5: Event Study Job Switchers



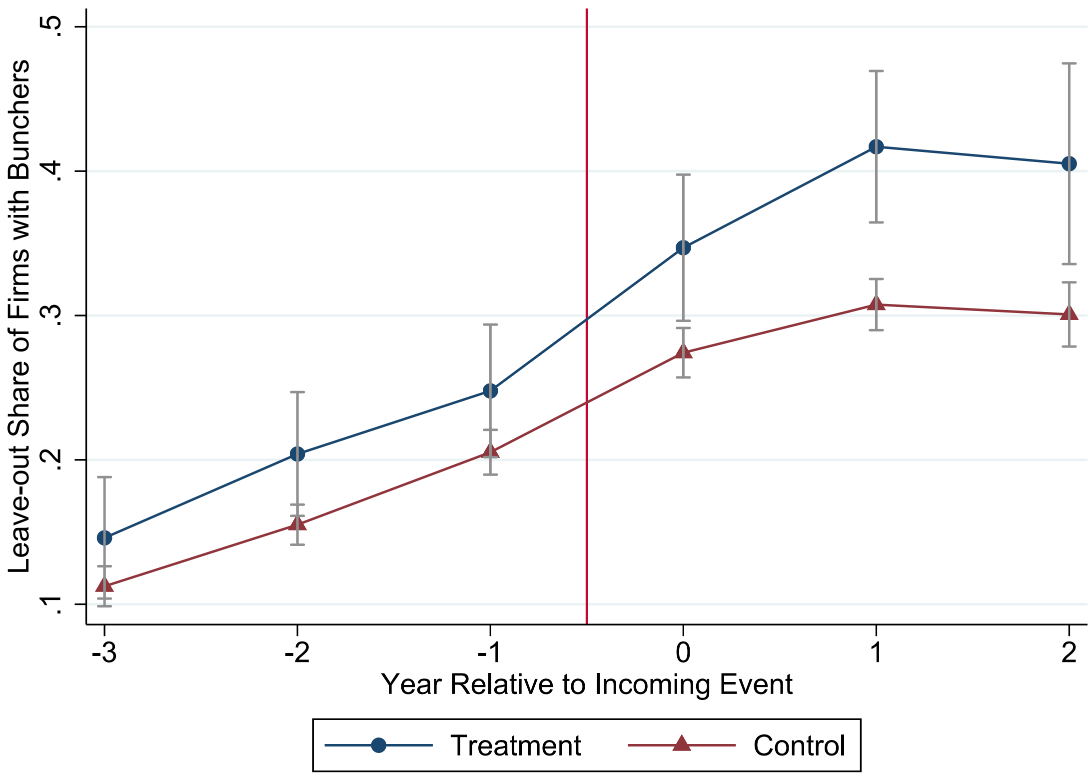
This figure shows an event study with bunching shares of job switchers around the time of the job transition. The vertical line indicates the time of the transition. We observe bunching among individuals who come from a firm in the medium quintile of the distribution of co-worker bunching shares and differentiate between those who switch to a firm in the bottom, medium, and top quintile.

Figure 6: Event Study Job Switchers – Sample of Displaced Workers



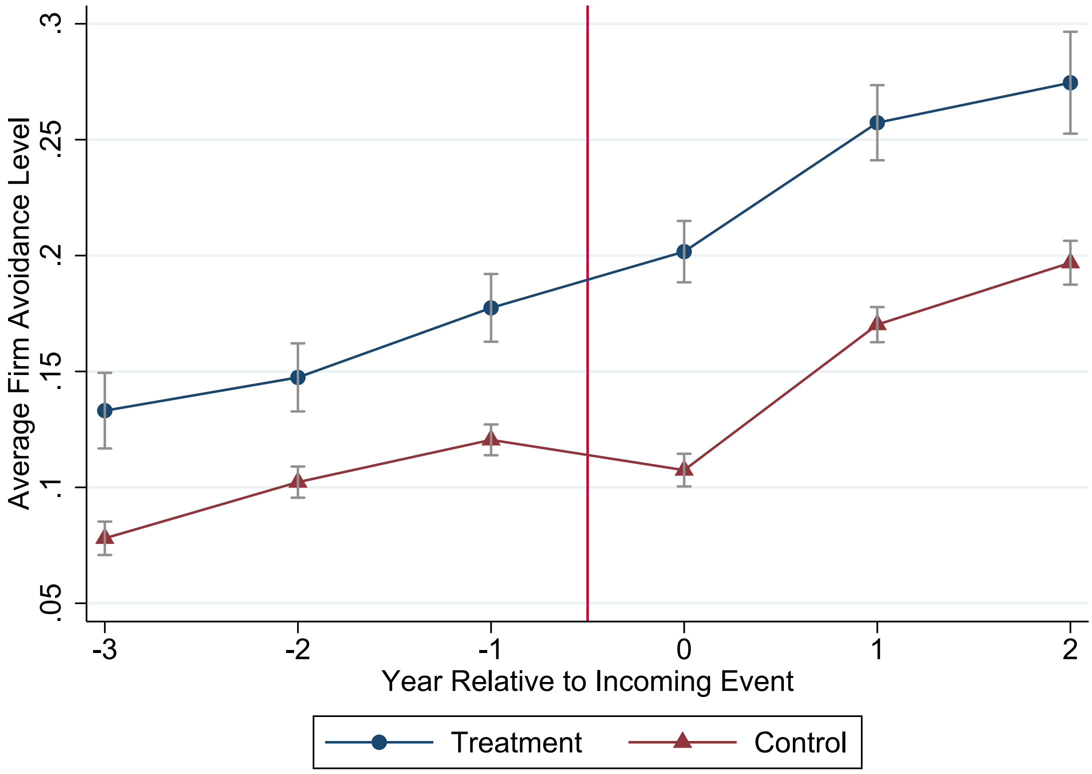
This figure shows an event study with bunching shares of job switchers around the time of the job transition in the subsample of workers who exogenously loose their job due to a firm closure.

Figure 7: Peer Learning Event Study



This figure shows an event study on the firm level with the share of firms employing bunchers around the hiring of a new co-worker (leaving out the new worker from the calculation). The vertical line denotes the arrival of the new worker. The treatment group is formed by firms that receive a new co-worker who was bunching in her previous firm while the control group is formed by firms with a new co-worker who was not bunching (despite being a potential buncher with gross income in the range above the kink).

Figure 8: Experts Event Study



This figure shows an event study on the firm level with the average share of bunchers around the entry of a new accountant into the firm. The vertical line denotes the arrival of the new accountant. The treatment group is formed by firms that receive an accountant who was previously working for a firm with bunchers while the control group is formed by firms with a new accountant who was working for a firm without any bunchers.

Supplemental Online Appendix

A Institutional Details

Table A.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%.

Figure A.1: Tax Declaration Form F107 for Wage Earners

SERVICIO DE RENTAS INTERNAS 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.2: Tax Declaration Form for Projecting Decuctions

...le hace bien al país!

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

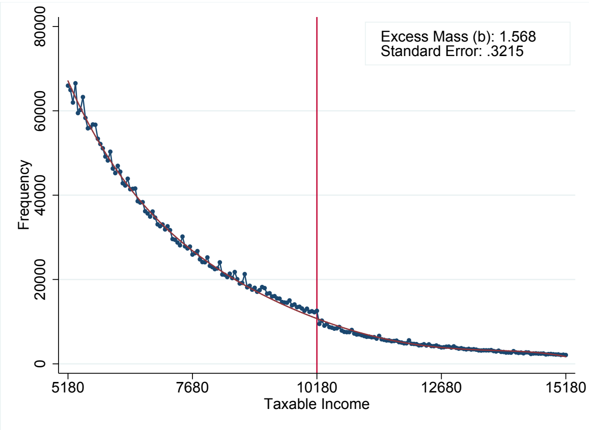
EMPLEADOR / AGENTE DE RETENCION	**EMPLEADO CONTRIBUYENTE**
	FIRMA DEL SERVIDOR

B Subgroup Analyses

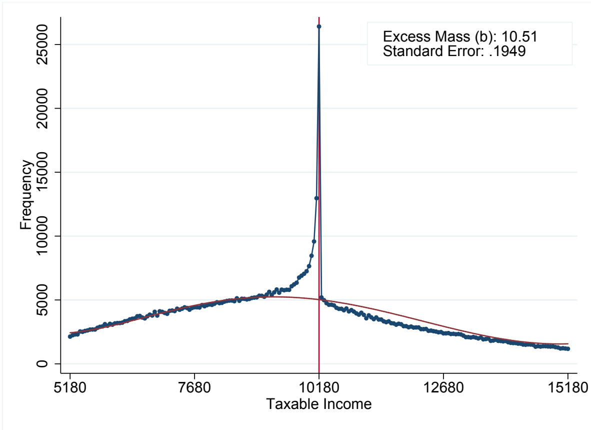
Further evidence for the fact that bunching is driven by reporting behavior can be found in Figure B.1. Individuals who do not file deductions for personal expenses do not display high levels of bunching (Figure B.1a). In contrast, individuals who file deductions (Figure B.1b) form a substantial excess 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 B.3). 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 B.2. The left panel shows bunching shares among workers who start from a firm in the lower quintile of the bunching distribution while the right panel refers to movers who start in the upper quintile. Among workers starting in the lower bunching quintile we see very similar patterns as before: individuals who move to the high quintile experience strong and sustained increases in bunching, whereas individuals moving to the low or mid quintile exhibit much smaller increases. Considering workers starting in the high 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 B.1: The impact of filing deductions

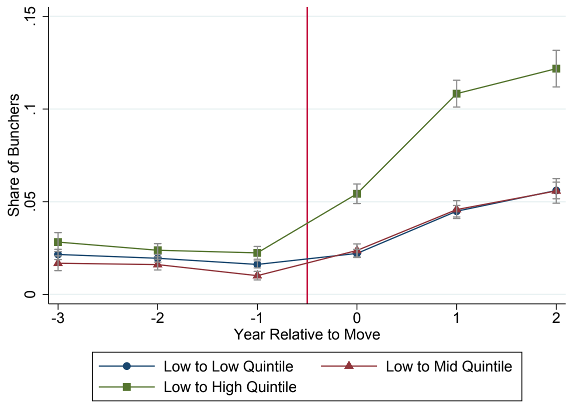


(a) No Deductions

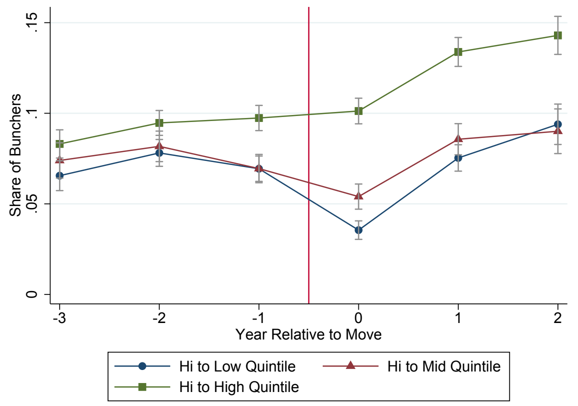


(b) With Deductions

Figure B.2: Event Study Job Switchers



(a) from low bunching



(b) from high bunching

Figure B.3: Bunching Estimates Gross Income

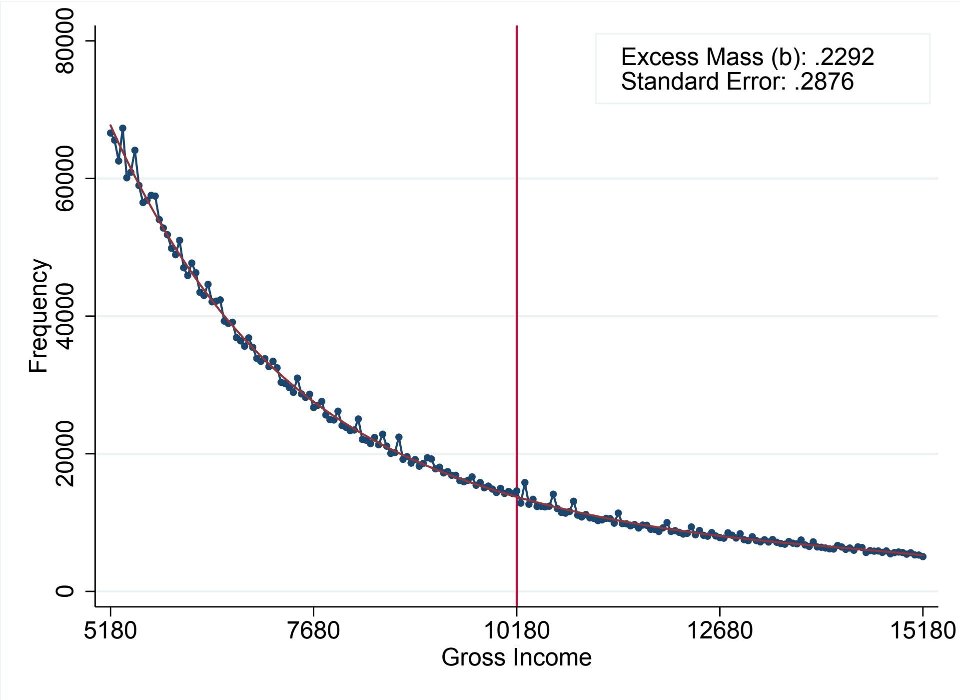
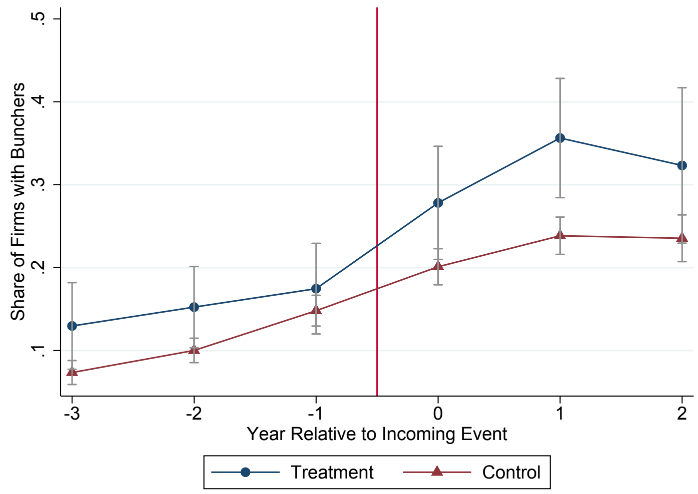
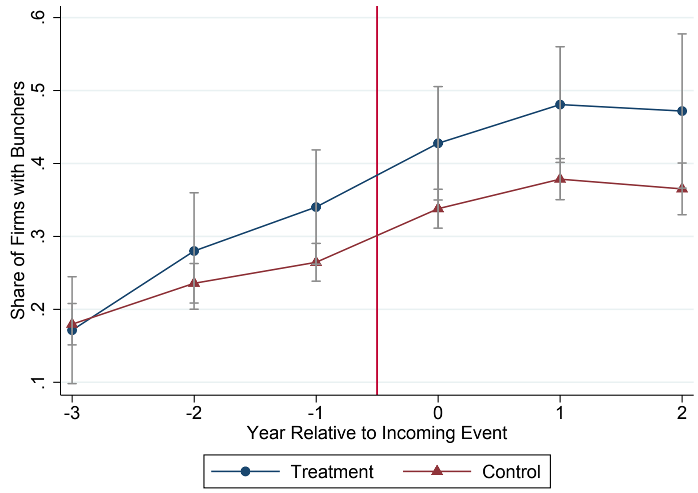


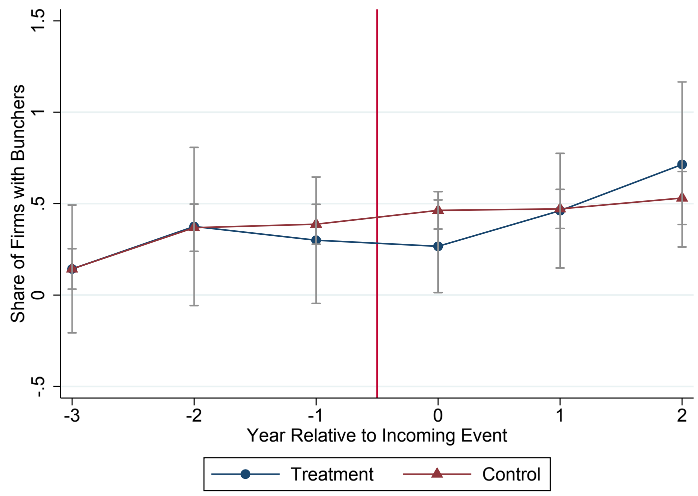
Figure B.4: Peer Learning Event Study - Firm Size



(a) Small Firms



(b) Medium Sized Firms



(c) Large Firms

C Robustness Checks: Outcomes

In this section, we perform the entire analyses of the main part for two different measures of tax avoidance. Our base measure of tax avoidance, bunching at the first kink in the tax schedule, is subject to an ad hoc choice of the bunching window around the kink (in our choice $1000 to the left of the kink). To check robustness with respect to this measure, we perform the different analyses using a more general indicator for avoiding tax payments that turns on if taxable income is below the first kink while gross income is above the first kink.

Our second robustness check employs an even more general measure of tax avoidance, the filing of deductions. Hence, we perform the analysis using an indicator whether an individual files any deduction.

C.1 Taxable Income below Kink

Table C.1: Bunching Individuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience exper	0.0086	0.055	0.082	0.089	0.031	0.029	0.028
	(.)	(0.0037)	(0.0042)	(0.0042)	(0.0091)	(0.0088)	(0.011)
Experience^2		-0.0053	-0.012	-0.014	-0.0042	-0.0037	0.0014
		(0.00027)	(0.0013)	(0.0012)	(0.0020)	(0.0020)	(0.0025)
Experience^3			0.00050	0.00061	0.00010	0.000070	-0.00023
			(0.000097)	(0.000091)	(0.00013)	(0.00013)	(0.00016)
Married				0.015	0.012	0.010	
				(0.0038)	(0.0042)	(0.0034)	
Age				0.0073	0.0030	0.0039	
				(0.0014)	(0.0022)	(0.0015)	
Age^2				-0.000084	-0.000040	-0.000050	
				(0.000014)	(0.000022)	(0.000015)	
Female				0.020	0.024	0.016	
				(0.0056)	(0.0066)	(0.0052)	
Secondary Education				0.087	0.071	0.047	
				(0.016)	(0.018)	(0.018)	
Tertiary Education				0.11	0.080	0.053	
				(0.016)	(0.018)	(0.019)	
Foreign				0.0028	-0.011	-0.016	
				(0.0065)	(0.0081)	(0.0074)	
Number of Jobs				-0.091	-0.094	-0.092	-0.074
				(0.0046)	(0.0048)	(0.0039)	(0.0023)
Log Gross Income					0.084	0.085	0.11
					(0.0069)	(0.0057)	(0.0072)
Gross Income Growth					-0.0094	-0.0096	-0.019
					(0.0034)	(0.0033)	(0.0050)
Corporate Firm						0.0016	0.017
						(0.0065)	(0.0046)
Firm Age						0.000022	-0.00015
						(0.00041)	(0.00012)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
Worker FE	No	No	No	No	No	No	Yes
R^2	0.067	0.071	0.071	0.093	0.089	0.095	0.423
Observations	618,356	618,356	618,356	618,356	508,417	508,417	508,417

The table shows results from linear regressions with a binary indicator for taxable income below the first kink (while gross income above the first kink) as dependent variable. The sample is restricted to potential bunchers in 2008 to 2015. Further (unreported) control variables include firmsize, firm age. Standard errors (in parentheses) are clustered at the firm level.

Table C.2: Job Switchers - Descriptives

	Descriptive Statistics						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	From Mid	Mid to Low	Diff	Matched Diff	Mid to High	Diff	Matched Diff
Demographics							
Age	31.63	32.90	1.87	-0.20	30.58	-0.45	0.25
	(8.76)	(9.40)	(0.15)	(0.15)	(7.99)	(0.15)	(0.16)
Married	0.45	0.43	-0.01	0.01	0.48	0.04	0.02
	(0.50)	(0.50)	(0.01)	(0.01)	(0.50)	(0.01)	(0.01)
Female	0.24	0.22	-0.01	-0.00	0.29	0.06	-0.03
	(0.43)	(0.42)	(0.01)	(0.01)	(0.45)	(0.01)	(0.01)
Tertiary Education	0.19	0.17	0.01	0.00	0.26	0.11	-0.04
	(0.39)	(0.37)	(0.01)	(0.01)	(0.44)	(0.01)	(0.01)
Pre-Switch							
Gross Income	5964.57	5350.51	-467.12	-33.99	7101.76	1284.14	109.97
	(5734.17)	(5431.36)	(86.60)	(84.85)	(6745.05)	(106.88)	(131.24)
Taxable Income	5665.17	5109.49	-439.23	-2.23	6670.02	1121.30	171.70
	(4917.99)	(4636.13)	(73.78)	(72.12)	(5845.90)	(91.82)	(111.60)
Share Deduction Filers	0.05	0.04	-0.01	0.00	0.09	0.04	0.01
	(0.23)	(0.20)	(0.00)	(0.00)	(0.28)	(0.00)	(0.01)
Buncher	0.03	0.02	-0.01	0.00	0.04	0.01	0.01
	(0.17)	(0.14)	(0.00)	(0.00)	(0.20)	(0.00)	(0.00)
Post-Switch							
Gross Income	6288.45	5053.08	-1206.54	-103.47	8185.55	1925.92	247.28
	(5587.02)	(4607.13)	(82.79)	(72.34)	(6482.91)	(108.03)	(133.81)
Taxable Income	5822.17	4893.36	-994.87	-76.67	7120.04	1231.81	-97.42
	(4560.98)	(4053.18)	(69.86)	(62.76)	(5048.67)	(86.25)	(104.94)
Share Deduction Filers	0.09	0.03	-0.03	-0.00	0.23	0.16	0.12
	(0.29)	(0.18)	(0.00)	(0.00)	(0.42)	(0.01)	(0.01)
Buncher	0.04	0.02	-0.01	0.00	0.07	0.04	0.02
	(0.19)	(0.15)	(0.00)	(0.00)	(0.25)	(0.00)	(0.00)
Observations	19,968	7,560			5,035		

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 the share of co-workers with taxable income below the first kink (and gross income above the kink) for any given year. Columns (2) to (4) represent individuals starting in the mid (third) quintile of the distribution of shares in the year before the move and moving to a firm in the low (first), mid (third) or high (fifth) quintile.

Table C.3: Job Switchers

	Mid to Low				Mid to High			
	(1) Full Sample	(2) Full Sample	(3) Matching	(4) Displaced	(5) Full Sample	(6) Full Sample	(7) Matching	(8) Displaced
A. Overall Effect								
After event year	-0.007	-0.004	-0.004	-0.023	0.110	0.104	0.094	0.101
	(0.003)	(0.003)	(0.004)	(0.012)	(0.009)	(0.007)	(0.009)	(0.018)
B. Effects by Relative Year								
Anticipatory Effects								
Event year - 3	0.006	0.004	0.003	0.005	-0.012	-0.012	-0.021	-0.008
	(0.004)	(0.004)	(0.005)	(0.016)	(0.006)	(0.005)	(0.012)	(0.015)
Event year - 2	0.000	-0.001	0.001	0.013	-0.007	-0.006	-0.014	-0.002
	(0.003)	(0.003)	(0.004)	(0.010)	(0.005)	(0.005)	(0.009)	(0.010)
Post Treatment Effects								
Event year	-0.007	-0.005	-0.004	-0.008	0.047	0.044	0.034	0.042
	(0.003)	(0.003)	(0.004)	(0.013)	(0.008)	(0.007)	(0.009)	(0.014)
Event year + 1	-0.008	-0.005	-0.003	-0.026	0.119	0.113	0.096	0.131
	(0.004)	(0.004)	(0.005)	(0.013)	(0.010)	(0.009)	(0.011)	(0.023)
Event year + 2	-0.001	0.001	-0.002	-0.020	0.187	0.179	0.161	0.143
	(0.006)	(0.006)	(0.008)	(0.018)	(0.016)	(0.015)	(0.018)	(0.034)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	70,292	70,292	68,988	8,084	59,294	59,294	47,089	8,278
C. Timing								
Event year - 2	0.005	-0.002		-0.005	0.006	0.001		-0.091
	(0.004)	(0.004)		(0.015)	(0.004)	(0.004)		(0.028)
Event year	-0.000	0.005		0.001	0.026	0.022		0.120
	(0.003)	(0.005)		(0.017)	(0.005)	(0.007)		(0.025)
Event year + 1	0.015	0.016		0.017	0.071	0.059		0.281
	(0.004)	(0.008)		(0.027)	(0.006)	(0.011)		(0.047)
Controls	No	Yes		Yes	No	Yes		Yes
Observations	25,048	25,048		1,499	23,947	23,947		1,559

The panels of this table denote the results from regression equations (1), (2) and (3) respectively with an indicator for taxable income below the first kink (and gross income above the first kink). Standard errors (in parentheses) are clustered at the destination firm by year level.

Table C.4: Extensive Margin of Firms with Taxable Income below Kink over time by cohort

	2008	2009	2010	2011	2012	2013	2014	2015	Obs
Cohort									
2008	0.33	0.52	0.61	0.62	0.74	0.79	0.81	0.81	489
2008	(0.47)	(0.50)	(0.49)	(0.49)	(0.44)	(0.41)	(0.39)	(0.39)	
2009		0.43	0.54	0.59	0.70	0.77	0.80	0.83	528
2009		(0.50)	(0.50)	(0.49)	(0.46)	(0.42)	(0.40)	(0.38)	
2010			0.38	0.51	0.66	0.73	0.76	0.79	555
2010			(0.48)	(0.50)	(0.48)	(0.44)	(0.43)	(0.41)	
2011				0.44	0.61	0.69	0.73	0.76	1100
2011				(0.50)	(0.49)	(0.46)	(0.44)	(0.43)	
2012					0.50	0.65	0.71	0.74	1657
2012					(0.50)	(0.48)	(0.45)	(0.44)	
2013						0.58	0.68	0.72	2203
2013						(0.49)	(0.47)	(0.45)	
2014							0.56	0.66	3280
2014							(0.50)	(0.47)	
2015								0.55	4847
2015								(0.50)	

Note: Share of firms in given cohort with at least one employee with taxable income below and gross income above the kink. Cohorts conditioned on the firm's year of entry into the formal sector. Further conditioned on employing potential bunchers in all subsequent years. Standard deviations given in parentheses.

Table C.5: Intensive Margin of Firms with Taxable Income below Kink over time by firm cohort

		2008	2009	2010	2011	2012	2013	2014	2015
Cohort									
2008	Share	0.39	0.52	0.51	0.47	0.51	0.56	0.58	0.62
2008	SD	(0.29)	(0.28)	(0.29)	(0.26)	(0.27)	(0.26)	(0.26)	(0.26)
2008	Obs	36	83	104	130	173	201	219	208
2009	Share		0.49	0.57	0.48	0.57	0.56	0.57	0.57
2009	SD		(0.27)	(0.27)	(0.28)	(0.28)	(0.25)	(0.27)	(0.26)
2009	Obs		41	79	113	134	159	181	179
2010	Share			0.53	0.51	0.54	0.56	0.60	0.64
2010	SD			(0.31)	(0.27)	(0.27)	)0.27)	(0.26)	(0.25)
2010	Obs			30	77	101	140	159	160
2011	Share				0.47	0.53	0.56	0.59	0.62
2011	SD				(0.31)	(0.28)	(0.27)	(0.27)	(0.26)
2011	Obs				55	122	189	237	242
2012	Share					0.53	0.54	0.58	0.59
2012	SD					(0.28)	(0.26)	(0.26)	(0.28)
2012	Obs					77	158	247	266
2013	Share						0.57	0.57	0.62
2013	SD						(0.28)	(0.29)	(0.26)
2013	Obs						94	207	240
2014	Share							0.54	0.62
2014	SD							(0.29)	(0.27)
2014	Obs							133	200
2015	Share								0.61
2015	SD								(0.28)
2015	Obs								96

Note: Average share of employees with taxable income below and gross income above the kink among those with gross income in a range where it is possible to reduce taxable income below the kink. Average values for the subset of firms with at least one employee with taxable income below but gross income above the kink. 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 at least 5 potential bunchers leads to a yearly changing composition of the cohort. Standard deviations given in parentheses.

Table C.6: Information Transmission: Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Below Kink	0.064	0.042	0.024		0.042	0.040	0.019	0.025		0.019
	(0.0075)	(0.0100)	(0.013)		(0.0099)	(0.017)	(0.020)	(0.022)		(0.020)
Incoming Below Kink above p90		0.047	0.060		0.045		0.052	0.047		0.052
		(0.012)	(0.013)		(0.012)		(0.028)	(0.029)		(0.028)
Incoming Below Kink between p50 and p90			0.034					-0.014		
			(0.014)					(0.028)		
Knowledgeable Accountant				0.040	0.039				0.057	0.057
				(0.0057)	(0.0057)				(0.0082)	(0.0082)
Avg. Age	-0.0028	-0.0028	-0.0028	-0.0029	-0.0028	-0.0014	-0.0014	-0.0014	-0.0015	-0.0014
	(0.00056)	(0.00056)	(0.00056)	(0.00056)	(0.00056)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Share Female	0.037	0.037	0.037	0.037	0.038	0.024	0.025	0.024	0.024	0.026
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Between 25 and 250 Employees	0.037	0.037	0.037	0.047	0.038	0.061	0.062	0.062	0.063	0.062
	(0.0065)	(0.0065)	(0.0065)	(0.0063)	(0.0065)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
More than 250 Employees	0.10	0.096	0.096	0.13	0.097	0.16	0.16	0.16	0.17	0.16
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Manufacturing	0.051	0.051	0.051	0.055	0.051					
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)					
Construction	0.041	0.041	0.041	0.042	0.041					
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)					
Trade; Repairing	0.060	0.061	0.060	0.063	0.062					
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)					
Hotel and Restaurant	0.013	0.013	0.013	0.011	0.011					
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)					
Transport, Storage, Communication	0.043	0.043	0.043	0.046	0.044					
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)					
Financial Sector	0.078	0.078	0.078	0.086	0.082					
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)					
Real Estate, Business and Renting	0.051	0.051	0.050	0.052	0.051					
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)					
Education	0.0015	0.0018	0.0013	0.0029	0.0041					
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)					
Health and Social Services	0.052	0.051	0.051	0.054	0.053					
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)					
Other	0.043	0.043	0.043	0.048	0.045					
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	35025	35025	35025	35025	35025	35025	35025	35025	35025	35025

The outcome variable is a binary indicator for a firm having at least one avoider with taxable income below but gross income above kink. Further time-varying controls: lagged bunching behavior, share married, share with tertiary education, average gross income at firm, as well as year and province fixed effects.

Table C.7: Information Transmission: Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Below Kink	-0.023	-0.013	-0.022		-0.013	-0.012	-0.011	-0.014		-0.011
	(0.010)	(0.013)	(0.016)		(0.013)	(0.016)	(0.019)	(0.020)		(0.019)
Incoming Below Kink above p90		-0.018	-0.012		-0.019		-0.0015	0.00071		-0.0015
		(0.016)	(0.017)		(0.016)		(0.024)	(0.024)		(0.024)
Incoming Below Kink between p50 and p90			0.015					0.0070		
			(0.016)					(0.024)		
Knowledgeable Accountant				0.0080	0.0090				-0.0031	-0.0030
				(0.0089)	(0.0089)				(0.011)	(0.011)
Avg. Age	-0.00033	-0.00036	-0.00036	-0.00013	-0.00030	0.0038	0.0038	0.0039	0.0039	0.0039
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Share Female	0.11	0.11	0.11	0.11	0.11	0.041	0.041	0.041	0.043	0.041
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.092)	(0.092)	(0.092)	(0.092)	(0.092)
Between 25 and 250 Employees	-0.051	-0.051	-0.052	-0.056	-0.051	-0.030	-0.030	-0.031	-0.031	-0.031
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
More than 250 Employees	-0.17	-0.17	-0.17	-0.18	-0.17	-0.063	-0.063	-0.064	-0.065	-0.063
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Manufacturing	0.028	0.028	0.029	0.027	0.029					
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)					
Construction	0.0078	0.0079	0.0074	0.0078	0.0079					
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)					
Trade; Repairing	0.050	0.050	0.049	0.050	0.050					
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)					
Hotel and Restaurant	0.027	0.027	0.027	0.027	0.026					
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)					
Transport, Storage, Communication	0.036	0.035	0.035	0.035	0.035					
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)					
Financial Sector	0.040	0.040	0.040	0.039	0.041					
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)					
Real Estate, Business and Renting	0.028	0.028	0.028	0.028	0.028					
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)					
Education	-0.068	-0.069	-0.070	-0.067	-0.069					
	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)					
Health and Social Services	0.0020	0.0034	0.0033	0.0041	0.0036					
	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)					
Other	0.019	0.019	0.018	0.018	0.019					
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	7264	7264	7264	7264	7264	7264	7264	7264	7264	7264

The outcome variable is the share of avoiders among potential bunchers. Further controls: lagged bunching behavior, share married, share with tertiary education, average gross income at firm, as well as year and province fixed effects. Standard errors clustered at firm level.

Table C.8: Peer Learning Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.02	36.36	0.48	-0.31
	(6.03)	(6.14)	(0.24)	(0.30)
Share Married	0.52	0.52	0.01	0.00
	(0.24)	(0.23)	(0.01)	(0.01)
Share Female	0.37	0.39	0.03	-0.03
	(0.27)	(0.26)	(0.01)	(0.01)
Share Tertiary Education	0.32	0.34	0.02	0.01
	(0.26)	(0.27)	(0.01)	(0.01)
Pre-Event				
Firmsize	50.74	50.82	0.10	-2.73
	(120.13)	(96.22)	(4.84)	(6.30)
Corporate Firm	0.85	0.87	0.03	-0.00
	(0.36)	(0.34)	(0.01)	(0.02)
Avg Gross Income	6903.01	7528.15	888.66	252.44
	(4052.51)	(4359.96)	(162.46)	(209.82)
Avg Taxable Income	6231.00	6658.35	607.49	148.79
	(3177.46)	(3310.22)	(127.53)	(160.47)
Share with Avoiders	0.33	0.39	0.09	0.05
	(0.47)	(0.49)	(0.02)	(0.02)
Post-Event				
Avg Gross Income	7761.76	8193.82	614.19	178.71
	(3949.91)	(4171.53)	(158.74)	(198.53)
Avg Taxable Income	6925.06	7135.82	299.60	45.20
	(3073.59)	(3062.69)	(123.71)	(149.11)
Share with Avoiders	0.41	0.49	0.12	0.07
	(0.49)	(0.50)	(0.02)	(0.02)
Observations	2,954	876		

Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the peer learning channel. The sample consists of all firms receiving one incoming employee between 2010 and 2014 and for which it is possible to observe at least two consecutive years before and after the event. Treated refers to firms receiving incoming avoiders with taxable income below but gross income above the kink prior to joining their new firm. Column (3) displays the difference between treated and control and column (4) this same difference for the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, corporate status of firm and average gross income pre and post event. Pre-event refers to the year before the arrival of new co-workers and post-event to the first year after the arrival of the new coworkers.

Table C.9: Peer Learning - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.036	0.033	0.035
	(0.016)	(0.016)	(0.021)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	0.023	0.025	0.039
	(0.017)	(0.017)	(0.022)
Post Treatment Effects			
Event year	0.052	0.049	0.051
	(0.019)	(0.019)	(0.025)
Event year + 1	0.040	0.038	0.040
	(0.021)	(0.021)	(0.027)
Event year + 2	0.038	0.038	0.060
	(0.028)	(0.027)	(0.037)
Controls	No	Yes	Yes
Observations	15,913	15,913	9,418

Notes: The table reports results from the event-study regression equation (5) at the firm level. Outcome variable is the leave-out firm avoidance decision and event year refers to the year of incoming employees. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, corporate status of firm, as well as industry and province dummies and dummies for the year of the incoming event. Standard errors (in parentheses) are clustered at the firm level.

Table C.10: Experts Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.00	36.07	-0.03	0.06
	(7.40)	(7.29)	(0.15)	(0.18)
Share Married	0.47	0.47	-0.00	0.01
	(0.28)	(0.27)	(0.01)	(0.01)
Share Female	0.41	0.41	0.00	-0.00
	(0.30)	(0.30)	(0.01)	(0.01)
Share Tertiary Education	0.28	0.28	-0.00	0.01
	(0.28)	(0.27)	(0.01)	(0.01)
Pre-Event				
Firmsize	43.99	49.11	7.87	-2.07
	(178.40)	(224.39)	(3.63)	(5.25)
Avg Gross Income	5217.38	5801.08	783.54	29.86
	(4529.22)	(4891.55)	(92.75)	(122.52)
Avg Taxable Income	4766.13	5215.96	597.02	-12.16
	(3671.01)	(3929.51)	(75.36)	(98.88)
Share with below	0.21	0.26	0.07	0.02
	(0.41)	(0.44)	(0.01)	(0.01)
Post-Event				
Avg Gross Income	5227.81	5882.51	907.73	176.91
	(4668.04)	(5166.17)	(84.52)	(120.25)
Avg Taxable Income	4770.90	5267.86	691.88	127.25
	(3837.20)	(4128.78)	(69.57)	(95.53)
Share with below	0.21	0.27	0.09	0.03
	(0.41)	(0.45)	(0.01)	(0.01)
Observations	16,389	4,201		

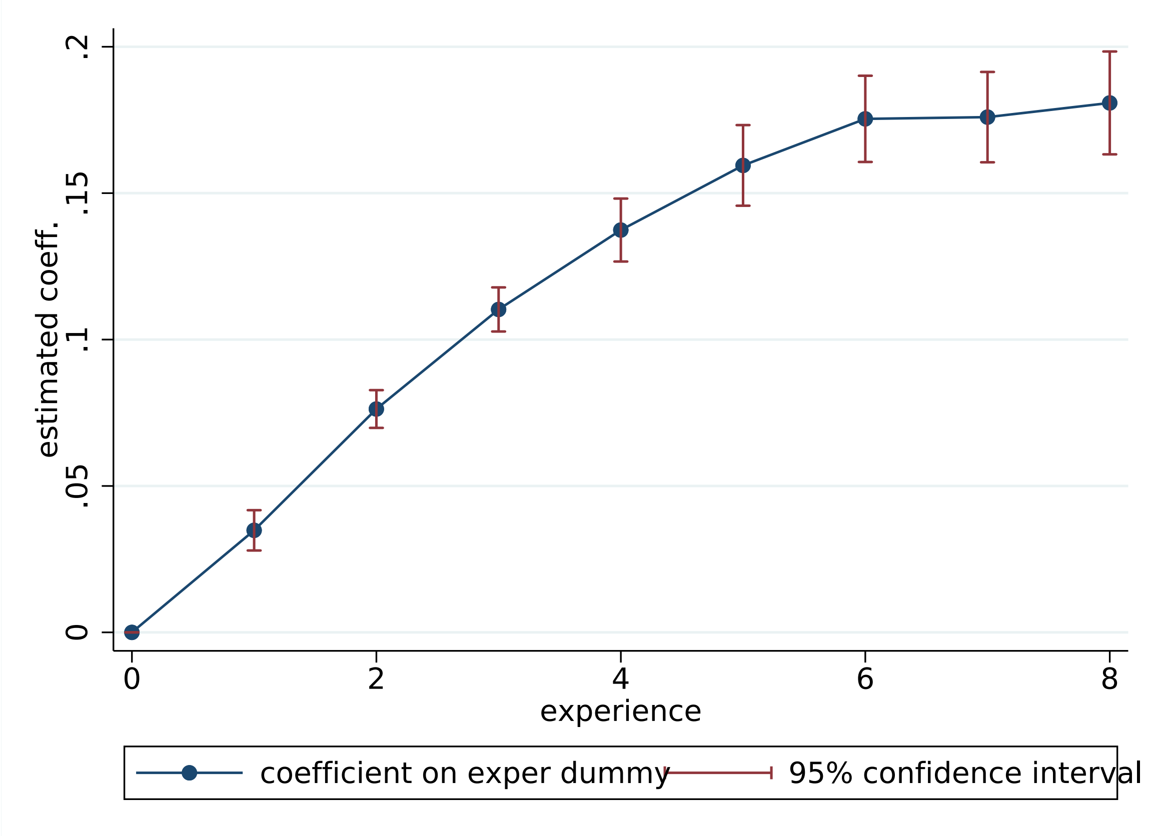
Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the experts channel. The sample is based on the universe of accountant switches between 2010 and 2014 for which it is possible to observe at least two consecutive years before and after the event and the firms employ potential bunchers throughout. Cases in which firms simultaneously received knowledgeable and non-knowledgeable accountants were excluded. Treated refers to firms receiving new accountants previously working at a firm in which employees were avoiding paying taxes by having taxable income below but gross income above the kink. Columns (3) displays the difference to a control group consisting of firms receiving an accountant previously working at a firm with potential bunchers but with zero tax avoiders. Column (4) displays the difference to the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, and average gross income pre and post event. Pre-event refers to the year before the arrival of the new accountants and post-event to the first year after the arrival of the new accountants.

Table C.11: Experts Event Study - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.119	0.015	0.014
	(0.007)	(0.008)	(0.013)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	-0.013	-0.000	-0.003
	(0.007)	(0.009)	(0.013)
Post Treatment Effects			
Event year	0.078	0.014	0.008
	(0.007)	(0.009)	(0.016)
Event year + 1	0.133	0.015	0.012
	(0.009)	(0.010)	(0.016)
Event year + 2	0.172	0.017	0.023
	(0.011)	(0.013)	(0.020)
Controls	No	Yes	Yes
Observations	60,483	60,483	28,243

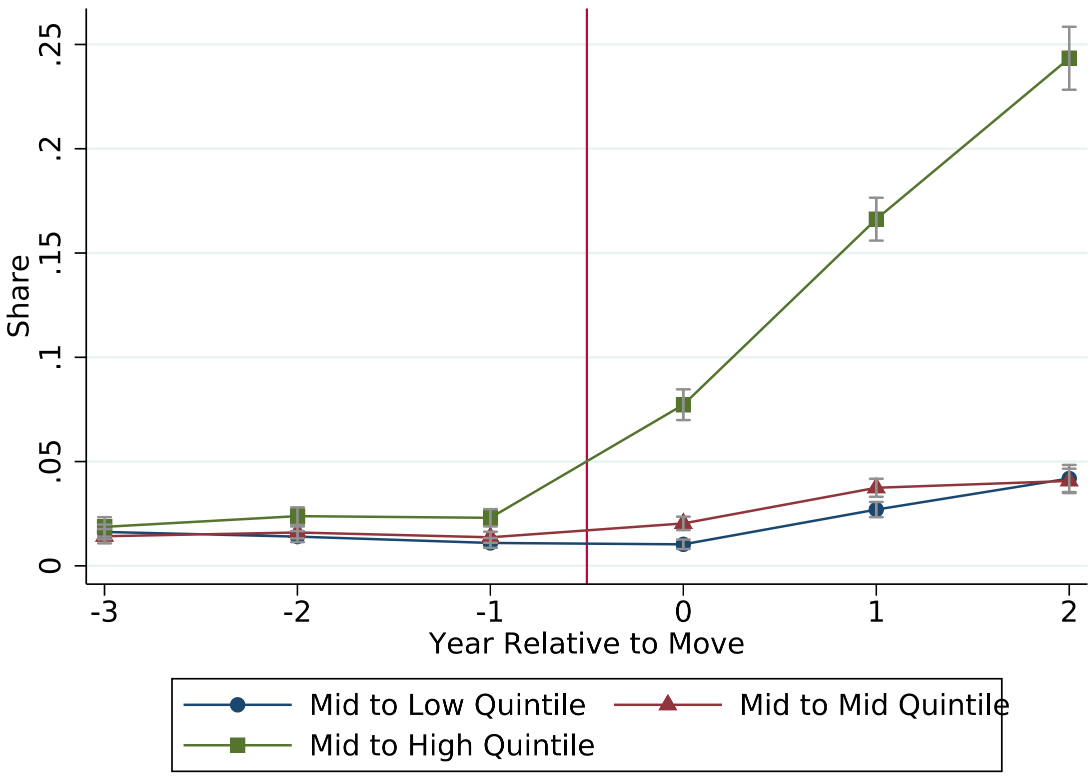
Notes: The table reports results from the event study regressions quantifying the experts channel detailed in Section (4.2.2). Outcome variable is the firm avoiding decision and event year refers to the year of the incoming accountant. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, as well as industry and province dummies and dummies for the year of the accountant switch. Standard errors (in parentheses) are clustered at the firm level.

Figure C.1: Coefficients on experience dummies



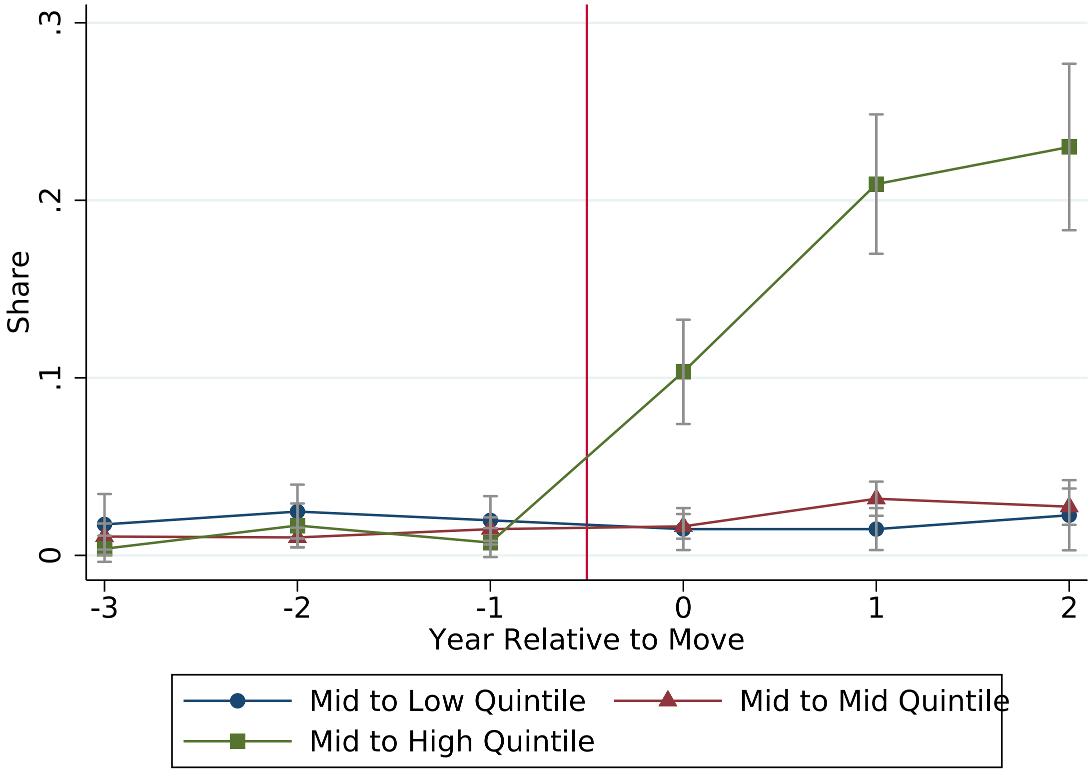
This figure depicts estimated coefficients from a linear regression of an avoiding indicator on dummy variables for each year of experience in the formal sector. We control for individual fixed effects, income dynamics and a broad range of firm characteristics.

Figure C.2: Event Study Job Switchers



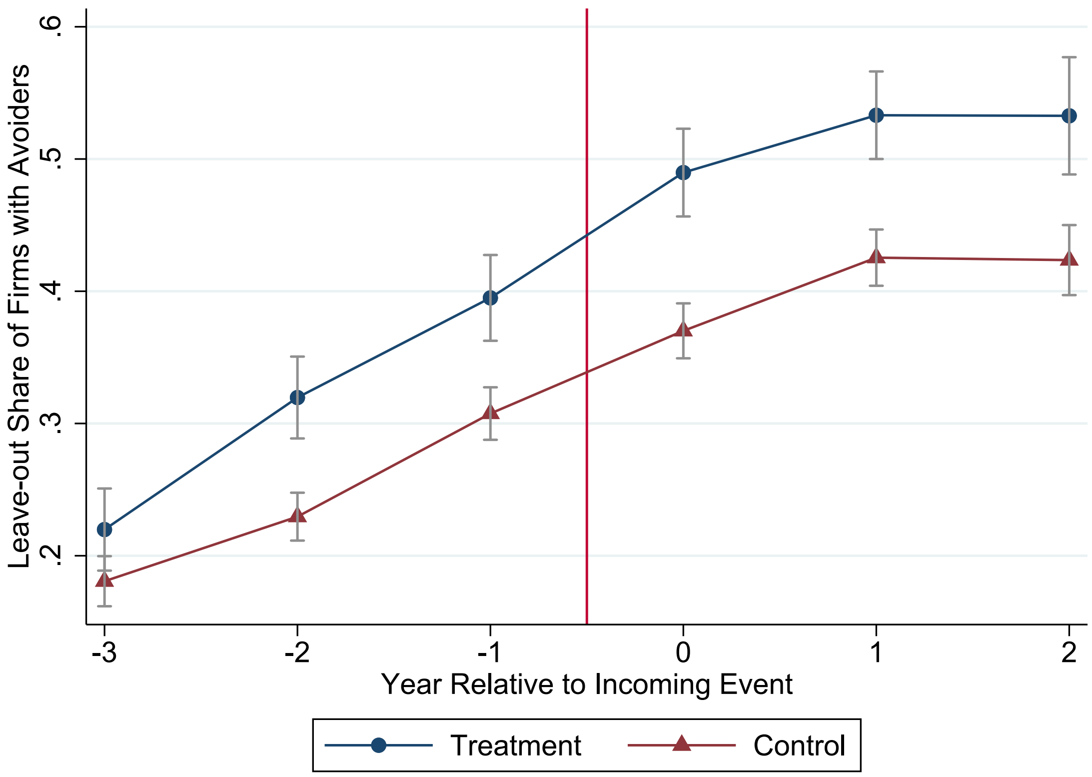
This figure shows an event study with avoiding shares of job switchers around the time of the job transition. The vertical line indicates the time of the transition. We observe avoiding among individuals who come from a firm in the medium quintile of the distribution of co-worker bunching shares and differentiate between those who switch to a firm in the bottom, medium, and top quintile.

Figure C.3: Event Study Job Switchers – Sample of Displaced Workers



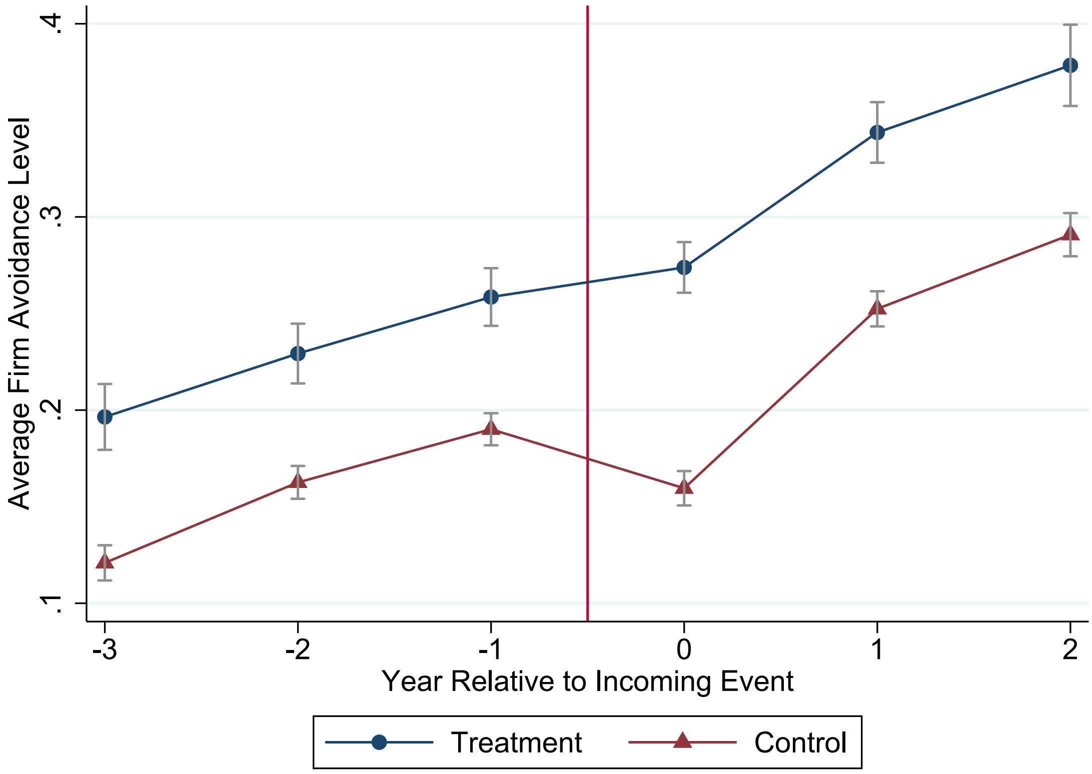
This figure shows an event study with avoiding shares of job switchers around the time of the job transition in the subsample of workers who exogenously loose their job due to a firm closure.

Figure C.4: Peer Learning Event Study



This figure shows an event study on the firm level with the share of firms employing avoiders around the hiring of a new co-worker (leaving out the new worker from the calculation). The vertical line denotes the arrival of the new worker. The treatment group is formed by firms that receive a new co-worker who was avoiding in her previous firm while the control group is formed by firms with a new co-worker who was not avoiding (despite being a potential avoider with gross income in the range above the kink).

Figure C.5: Experts Event Study



This figure shows an event study on the firm level with the average share of avoiders around the entry of a new accountant into the firm. The vertical line denotes the arrival of the new accountant. The treatment group is formed by firms that receive an accountant who was previously working for a firm with avoiders while the control group is formed by firms with a new accountant who was working for a firm without any avoiders.

C.2 Filing Deductions

Table C.12: Bunching Individuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Experience	0.029	0.10	0.15	0.16	-0.099	-0.10	-0.022
	(0.0023)	(0.0050)	(0.0075)	(0.0083)	(0.011)	(0.0097)	(0.0089)
Experience^2		-0.0084	-0.021	-0.023	0.020	0.020	0.014
		(0.00036)	(0.0014)	(0.0015)	(0.0021)	(0.0020)	(0.0019)
Experience^3			0.00092	0.0010	-0.0012	-0.0012	-0.00093
			(0.000093)	(0.000094)	(0.00013)	(0.00012)	(0.00012)
Married				0.025	0.012	0.010	
				(0.0046)	(0.0045)	(0.0036)	
Age				0.016	-0.0028	-0.0012	
				(0.0022)	(0.0030)	(0.0020)	
Age^2				-0.00019	0.0000039	-0.000010	
				(0.000022)	(0.000030)	(0.000021)	
Female				0.0077	0.018	0.014	
				(0.0080)	(0.0087)	(0.0067)	
Secondary Education				0.18	0.10	0.075	
				(0.021)	(0.024)	(0.023)	
Tertiary Education				0.26	0.15	0.12	
				(0.021)	(0.024)	(0.024)	
Foreign				0.061	0.021	0.018	
				(0.0090)	(0.0087)	(0.0080)	
Number of Jobs				-0.11	-0.093	-0.092	-0.080
				(0.0061)	(0.0063)	(0.0049)	(0.0026)
Log Gross Income					0.33	0.33	0.25
					(0.0050)	(0.0050)	(0.0050)
Gross Income Growth					-0.075	-0.075	-0.053
					(0.0021)	(0.0020)	(0.0026)
Corporate Firm						0.014	0.016
						(0.0081)	(0.0057)
Firm Age						-0.000046	-0.000013
						(0.00061)	(0.00017)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
Worker FE	No	No	No	No	No	No	Yes
R^2	0.138	0.145	0.145	0.180	0.305	0.312	0.606
Observations	618,356	618,356	618,356	618,356	508,417	508,417	508,417

The table shows results from linear regressions with a binary indicator for filing any deductions as dependent variable. The sample is restricted to potential bunchers in 2008 to 2015. Further (unreported) control variables include firmsize, firm age. Standard errors (in parentheses) are clustered at the firm level.

Table C.13: Job Switchers - Descriptives

	Descriptive Statistics						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	From Mid	Mid to Low	Diff	Matched Diff	Mid to High	Diff	Matched Diff
Demographics							
Age	31.66	33.43	2.37	-0.12	30.48	-0.58	0.03
	(8.92)	(9.74)	(0.16)	(0.18)	(7.94)	(0.15)	(0.16)
Married	0.46	0.45	-0.00	-0.01	0.48	0.03	0.01
	(0.50)	(0.50)	(0.01)	(0.01)	(0.50)	(0.01)	(0.01)
Female	0.27	0.25	-0.03	0.01	0.27	-0.01	-0.00
	(0.44)	(0.43)	(0.01)	(0.01)	(0.44)	(0.01)	(0.01)
Tertiary Education	0.20	0.18	0.02	-0.02	0.27	0.11	-0.03
	(0.40)	(0.39)	(0.01)	(0.01)	(0.44)	(0.01)	(0.01)
Pre-Switch							
Gross Income	5622.45	5089.50	-272.77	119.02	6581.08	1218.81	-152.99
	(4591.53)	(4464.57)	(73.19)	(74.25)	(5158.91)	(81.10)	(104.01)
Taxable Income	5375.94	4882.35	-271.50	52.78	6237.73	1083.89	-13.54
	(3925.14)	(3827.79)	(62.57)	(64.05)	(4398.04)	(69.13)	(86.26)
Share Deduction Filers	0.05	0.04	-0.00	0.01	0.07	0.03	-0.01
	(0.21)	(0.19)	(0.00)	(0.00)	(0.26)	(0.00)	(0.01)
Buncher	0.03	0.03	0.00	-0.00	0.05	0.02	0.01
	(0.18)	(0.16)	(0.00)	(0.00)	(0.21)	(0.00)	(0.00)
Post-Switch							
Gross Income	6259.49	4719.54	-1141.97	2.72	8541.21	2679.70	372.29
	(5122.91)	(3736.68)	(71.82)	(65.95)	(6297.83)	(94.57)	(124.52)
Taxable Income	5813.79	4627.89	-957.02	44.46	7463.84	1878.93	71.73
	(4216.59)	(3376.41)	(61.73)	(58.38)	(5025.47)	(76.93)	(99.78)
Share Deduction Filers	0.10	0.02	-0.03	-0.01	0.25	0.20	0.14
	(0.30)	(0.14)	(0.00)	(0.00)	(0.43)	(0.01)	(0.01)
Buncher	0.04	0.02	-0.01	0.00	0.07	0.04	0.02
	(0.19)	(0.15)	(0.00)	(0.00)	(0.25)	(0.00)	(0.00)
Observations	19,365	6,216			5,525		

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 the share of co-workers filing any deductions for any given year. Columns (2) to (4) represent individuals starting in the mid (third) quintile of the distribution of shares in the year before the move and moving to a firm in the low (first), mid (third) or high (fifth) quintile.

Table C.14: Job Switchers

	Mid to Low				Mid to High			
	(1) Full Sample	(2) Full Sample	(3) Matching	(4) Displaced	(5) Full Sample	(6) Full Sample	(7) Matching	(8) Displaced
A. Overall Effect								
After event year	-0.036	-0.026	-0.016	-0.025	0.264	0.240	0.197	0.223
	(0.005)	(0.005)	(0.006)	(0.016)	(0.015)	(0.011)	(0.016)	(0.025)
B. Effects by Relative Year								
Anticipatory Effects								
Event year - 3	0.005	0.000	-0.005	-0.037	-0.035	-0.025	-0.009	-0.057
	(0.006)	(0.006)	(0.006)	(0.022)	(0.009)	(0.008)	(0.016)	(0.025)
Event year - 2	0.005	0.000	-0.002	0.002	-0.021	-0.012	-0.017	0.005
	(0.004)	(0.004)	(0.006)	(0.015)	(0.007)	(0.007)	(0.015)	(0.020)
Post Treatment Effects								
Event year	-0.030	-0.024	-0.017	-0.025	0.169	0.159	0.150	0.222
	(0.005)	(0.005)	(0.006)	(0.016)	(0.021)	(0.016)	(0.020)	(0.060)
Event year + 1	-0.032	-0.025	-0.015	-0.019	0.283	0.261	0.215	0.223
	(0.006)	(0.006)	(0.007)	(0.019)	(0.016)	(0.014)	(0.019)	(0.033)
Event year + 2	-0.041	-0.036	-0.025	-0.062	0.335	0.308	0.219	0.186
	(0.009)	(0.008)	(0.011)	(0.021)	(0.018)	(0.019)	(0.025)	(0.077)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	65,694	65,694	56,447	7,740	63,225	63,225	51,604	7,570
C. Timing								
Event year - 2	0.005	-0.002		-0.029	0.006	0.001		-0.064
	(0.004)	(0.004)		(0.024)	(0.004)	(0.004)		(0.034)
Event year	-0.000	0.005		-0.005	0.026	0.022		0.173
	(0.003)	(0.005)		(0.022)	(0.005)	(0.007)		(0.045)
Event year + 1	0.015	0.016		0.025	0.071	0.059		0.221
	(0.004)	(0.008)		(0.037)	(0.006)	(0.011)		(0.064)
Controls	No	Yes		Yes	No	Yes		Yes
Observations	25,048	25,048		2,028	23,947	23,947		1,855

The panels of this table denote the results from regression equations (1), (2) and (3) respectively with an indicator for filing any deductions. Standard errors (in parentheses) are clustered at the destination firm by year level.

Table C.15: Extensive Margin of Firms with Deduction Filers over time by cohort

	2008	2009	2010	2011	2012	2013	2014	2015	Obs
Cohort									
2008	0.45	0.63	0.72	0.75	0.86	0.89	0.90	0.92	645
2008	(0.50)	(0.48)	(0.45)	(0.43)	(0.35)	(0.32)	(0.30)	(0.27)	
2009		0.57	0.70	0.75	0.82	0.88	0.89	0.91	699
2009		(0.50)	(0.46)	(0.43)	(0.38)	(0.33)	(0.31)	(0.28)	
2010			0.54	0.67	0.78	0.86	0.89	0.90	775
2010			(0.50)	(0.47)	(0.41)	(0.35)	(0.32)	(0.29)	
2011				0.55	0.75	0.84	0.87	0.88	1425
2011				(0.50)	(0.44)	(0.37)	(0.34)	(0.32)	
2012					0.65	0.81	0.86	0.86	2105
2012					(0.48)	(0.39)	(0.34)	(0.35)	
2013						0.71	0.82	0.83	2724
2013						(0.45)	(0.38)	(0.37)	
2014							0.72	0.80	3802
2014							(0.45)	(0.40)	
2015								0.68	4996
2015								(0.47)	

Note: Share of firms in given cohort with at least one employee filing deductions. Cohorts conditioned on the firm's year of entry into the formal sector and having employees with gross income above the kink in all subsequent years. Standard deviations given in parentheses.

Table C.16: Intensive Margin of Firms with Deduction Filers over time by firm cohort

		2008	2009	2010	2011	2012	2013	2014	2015
Cohort									
2008	Share	0.60	0.71	0.72	0.70	0.78	0.78	0.81	0.81
2008	SD	(0.31)	(0.27)	(0.27)	(0.25)	(0.24)	(0.24)	(0.22)	(0.22)
2008	Obs	64	129	174	220	258	301	324	327
2009	Share		0.71	0.78	0.75	0.79	0.81	0.81	0.82
2009	SD		(0.28)	(0.24)	(0.25)	(0.24)	(0.24)	(0.23)	(0.22)
2009	Obs		56	110	167	186	227	259	252
2010	Share			0.71	0.74	0.77	0.80	0.81	0.84
2010	SD			(0.28)	(0.25)	(0.23)	(0.23)	(0.23)	(0.21)
2010	Obs			48	126	172	221	271	266
2011	Share				0.68	0.77	0.78	0.80	0.82
2011	SD				(0.30)	(0.24)	(0.23)	(0.23)	(0.23)
2011	Obs				96	198	291	369	391
2012	Share					0.72	0.77	0.80	0.82
2012	SD					(0.28)	(0.24)	(0.23)	(0.23)
2012	Obs					141	288	394	410
2013	Share						0.75	0.78	0.82
2013	SD						(0.27)	(0.25)	(0.22)
2013	Obs						165	343	376
2014	Share							0.71	0.81
2014	SD							(0.28)	(0.25)
2014	Obs							206	332
2015	Share								0.79
2015	SD								(0.23)
2015	Obs								158

Note: Average share of employees filing deductions among those with gross income above the kink. Values for given cohort, conditional on firm having at least one employee filing deductions. Cohorts conditioned on year of entry into formal sector and having employees with gross income above the kink in all subsequent years. Further conditioned on firms employing at least 5 workers with gross income above the kink in given year. The number of observations varies between year of observation since the conditioning on having at least 5 workers with gross income above the kink leads to a yearly changing composition of the cohort. Standard deviations given in parentheses.

Table C.17: Information Transmission: Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Deducter	0.020	0.00066	0.012		0.00083	-0.016	-0.024	0.011		-0.023
	(0.0056)	(0.0074)	(0.0095)		(0.0073)	(0.013)	(0.015)	(0.017)		(0.015)
Incoming Deducter above p90		0.040	0.032		0.039		0.021	-0.0024		0.020
		(0.0083)	(0.0092)		(0.0083)		(0.021)	(0.021)		(0.021)
Incoming Deducter between p50 and p90			-0.022					-0.074		
			(0.0093)					(0.019)		
Knowledgeable Accountant				0.031	0.030				0.045	0.045
				(0.0050)	(0.0050)				(0.0068)	(0.0068)
Avg. Age	-0.0042	-0.0042	-0.0042	-0.0042	-0.0041	-0.0034	-0.0034	-0.0035	-0.0035	-0.0035
	(0.00052)	(0.00052)	(0.00052)	(0.00052)	(0.00052)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Share Female	0.030	0.030	0.031	0.031	0.031	-0.0046	-0.0043	-0.0046	-0.0018	-0.0018
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Between 25 and 250 Employees	0.029	0.028	0.029	0.033	0.029	0.054	0.054	0.055	0.053	0.054
	(0.0057)	(0.0057)	(0.0057)	(0.0055)	(0.0057)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
More than 250 Employees	0.078	0.072	0.073	0.088	0.073	0.13	0.13	0.13	0.13	0.13
	(0.010)	(0.011)	(0.010)	(0.0095)	(0.010)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)
Manufacturing	0.035	0.035	0.034	0.036	0.035					
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)					
Construction	0.021	0.021	0.021	0.021	0.021					
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)					
Trade; Repairing	0.027	0.027	0.028	0.028	0.028					
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)					
Hotel and Restaurant	0.018	0.018	0.018	0.016	0.017					
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)					
Transport, Storage, Communication	0.011	0.011	0.011	0.012	0.012					
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)					
Financial Sector	0.042	0.042	0.042	0.046	0.045					
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)					
Real Estate, Business and Renting	0.023	0.024	0.024	0.024	0.024					
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)					
Education	-0.032	-0.032	-0.031	-0.031	-0.030					
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)					
Health and Social Services	0.022	0.021	0.021	0.023	0.023					
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)					
Other	0.0085	0.0087	0.0088	0.011	0.011					
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	35025	35025	35025	35025	35025	35025	35025	35025	35025	35025

The outcome variable is a binary indicator for a firm having at least one deducter. Further time-varying controls: lagged bunching behavior, share married, share with tertiary education, average gross income at firm, as well as year and province fixed effects. Standard errors clustered at firm level.

Table C.18: Information Transmission: Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Incoming Deducter	0.018	0.0075	-0.024		0.0075	-0.035	-0.020	-0.050		-0.020
	(0.026)	(0.030)	(0.037)		(0.030)	(0.040)	(0.042)	(0.050)		(0.042)
Incoming Deducter above p90		0.020	0.039		0.020		-0.033	-0.012		-0.033
		(0.038)	(0.039)		(0.038)		(0.067)	(0.070)		(0.067)
Incoming Deducter between p50 and p90			0.056					0.070		
			(0.039)					(0.060)		
Knowledgeable Accountant				-0.0052	-0.0060				0.0085	0.0084
				(0.023)	(0.023)				(0.027)	(0.027)
Avg. Age	-0.015	-0.015	-0.015	-0.015	-0.015	-0.014	-0.014	-0.014	-0.014	-0.014
	(0.0034)	(0.0034)	(0.0034)	(0.0035)	(0.0034)	(0.0089)	(0.0090)	(0.0090)	(0.0089)	(0.0090)
Share Female	0.19	0.19	0.19	0.19	0.19	0.022	0.019	0.023	0.028	0.018
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Between 25 and 250 Employees	0.29	0.29	0.29	0.30	0.29	0.16	0.16	0.16	0.16	0.16
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
More than 250 Employees	0.30	0.30	0.29	0.31	0.30	0.26	0.25	0.25	0.25	0.26
	(0.050)	(0.050)	(0.050)	(0.049)	(0.050)	(0.073)	(0.072)	(0.072)	(0.071)	(0.072)
Manufacturing	0.012	0.011	0.012	0.012	0.011					
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)					
Construction	-0.077	-0.076	-0.078	-0.077	-0.076					
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)					
Trade; Repairing	-0.032	-0.032	-0.035	-0.033	-0.032					
	(0.067)	(0.066)	(0.067)	(0.067)	(0.066)					
Hotel and Restaurant	-0.073	-0.073	-0.072	-0.075	-0.072					
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)					
Transport, Storage, Communication	-0.17	-0.17	-0.17	-0.17	-0.17					
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)					
Financial Sector	-0.14	-0.14	-0.14	-0.14	-0.14					
	(0.097)	(0.097)	(0.097)	(0.098)	(0.097)					
Real Estate, Business and Renting	-0.091	-0.090	-0.092	-0.091	-0.090					
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)					
Education	-0.27	-0.27	-0.27	-0.27	-0.27					
	(0.083)	(0.083)	(0.083)	(0.084)	(0.083)					
Health and Social Services	-0.14	-0.14	-0.14	-0.14	-0.14					
	(0.087)	(0.088)	(0.087)	(0.087)	(0.088)					
Other	-0.076	-0.075	-0.077	-0.076	-0.075					
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)					
Firm FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	7264	7264	7264	7264	7264	7264	7264	7264	7264	7264

The outcome variable is the share of deducters at a firm. Further controls: lagged bunching behavior, share married, share with tertiary education, average gross income at firm, as well as year and province fixed effects. Standard errors clustered at firm level.

Table C.19: Peer Learning Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.02	36.11	0.15	0.15
	(6.03)	(6.04)	(0.22)	(0.24)
Share Married	0.52	0.52	0.01	0.00
	(0.24)	(0.23)	(0.01)	(0.01)
Share Female	0.37	0.38	0.03	-0.02
	(0.27)	(0.27)	(0.01)	(0.01)
Share Tertiary Education	0.32	0.34	0.03	0.01
	(0.26)	(0.27)	(0.01)	(0.01)
Pre-Event				
Firmsize	50.74	49.65	-1.93	-2.10
	(120.13)	(103.84)	(4.46)	(4.45)
Corporate Firm	0.85	0.87	0.03	0.01
	(0.36)	(0.34)	(0.01)	(0.01)
Avg Gross Income	6903.01	7489.99	1038.90	81.77
	(4052.51)	(4499.99)	(149.21)	(172.22)
Avg Taxable Income	6231.00	6626.24	699.54	-56.25
	(3177.46)	(3482.79)	(117.24)	(136.95)
Share with Deducters	0.39	0.45	0.10	0.03
	(0.49)	(0.50)	(0.02)	(0.02)
Post-Event				
Avg Gross Income	7761.76	8205.73	785.80	61.69
	(3949.91)	(4199.75)	(145.90)	(164.29)
Avg Taxable Income	6925.06	7167.07	428.33	-99.44
	(3073.59)	(3155.16)	(113.82)	(126.60)
Share with Deducters	0.47	0.54	0.11	0.06
	(0.50)	(0.50)	(0.02)	(0.02)
Observations	2,954	1,285		

Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the peer learning channel. The sample consists of all firms receiving one incoming employee between 2010 and 2014 and for which it is possible to observe at least two consecutive years before and after the event. Treated refers to firms receiving incoming co-workers using deductions prior to joining their new firm. Column (3) displays the difference between treated and control and column (4) this same difference for the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, corporate status of firm and average gross income pre and post event. Pre-event refers to the year before the arrival of new co-workers and post-event to the first year after the arrival of the new coworkers.

Table C.20: Peer Learning - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.022	0.023	0.049
	(0.015)	(0.015)	(0.020)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	0.022	0.028	0.038
	(0.015)	(0.015)	(0.019)
Post Treatment Effects			
Event year	0.031	0.035	0.045
	(0.017)	(0.017)	(0.023)
Event year + 1	0.037	0.040	0.079
	(0.019)	(0.019)	(0.025)
Event year + 2	0.014	0.018	0.069
	(0.024)	(0.024)	(0.032)
Controls	No	Yes	Yes
Observations	15,913	15,913	13,847

Notes: The table reports results from the event-study regression equation (5) at the firm level. Outcome variable is the leave-out firm deduction decision and event year refers to the year of incoming employees. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, corporate status of firm, as well as industry and province dummies and dummies for the year of the incoming event. Standard errors (in parentheses) are clustered at the firm level.

Table C.21: Experts Event Study - Descriptives

	Descriptive Statistics			
	(1)	(2)	(3)	(4)
	Full Sample	Treated	Diff	Matched Diff
Demographics				
Avg Age	36.00	36.10	0.02	-0.15
	(7.40(	(7.28)	(0.15)	(0.17)
Share Married	0.47	0.47	0.00	0.00
	(0.28)	(0.27)	(0.0)1	(0.01)
Share Female	0.41	0.41	0.00	-0.00
	(0.30)	(0.30)	(0.01)	(0.01)
Share Tertiary Education	0.28	0.28	-0.01	0.01
	(0.28)	(0.27)	(0.01)	(0.01)
Pre-Event				
Firmsize	43.99	47.12	5.42	-2.61
	(178.40)	(211.66)	(3.49)	(4.80)
Avg Gross Income	5217.38	5813.76	848.54	55.52
	(4529.22)	(5080.19)	(89.15)	(115.40)
Avg Taxable Income	4766.13	5232.50	656.64	11.70
	(3671.01)	(4117.10)	(72.43)	(93.26)
Share using Deductions	0.27	0.32	0.09	0.02
	(0.44)	(0.47)	(0.01)	(0.01)
Post-Event				
Avg Gross Income	5227.81	5887.27	968.05	100.96
	(4668.04)	(5437.23)	(81.09)	(119.54)
Avg Taxable Income	4770.90	5285.93	758.88	96.06
	(3837.20)	(4415.80)	(66.74)	(96.23)
Share using Deductions	0.27	0.33	0.10	0.04
	(0.44)	(0.47)	(0.01)	(0.01)
Observations	16,389	4,824		

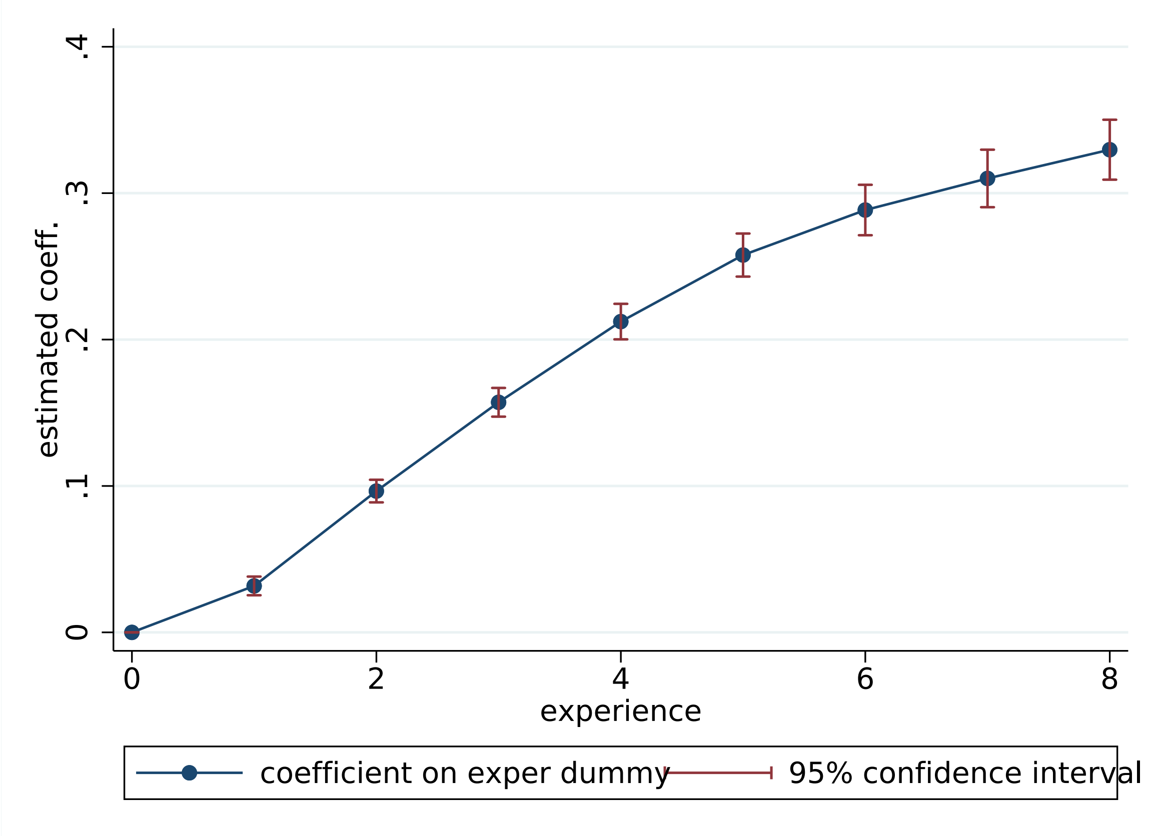
Notes: This table shows descriptive statistics for the sample of firms used in the event study quantifying the experts channel. The sample is based on the universe of accountant switches between 2010 and 2014 for which it is possible to observe at least two consecutive years before and after the event and the firms employ potential bunchers throughout. Cases in which firms simultaneously received knowledgeable and non-knowledgeable accountants were excluded. Treated refers to firms receiving new accountants previously working at a firm in which employees were using deductions. Columns (3) displays the difference to a control group consisting of firms receiving an accountant previously working at a firm with potential bunchers but zero employees using deductions. Column (4) displays the difference to the matched sample. Matching was done on average age, share married, female and tertiary educated, firmsize, and average gross income pre and post event. Pre-event refers to the year before the arrival of the new accountants and post-event to the first year after the arrival of the new accountants.

Table C.22: Experts Event Study - Regression Results

	(1)	(2)	(3)
	Full Sample		Matching
A. Overall Effect			
DiD estimate	0.130	0.015	0.031
	(0.007)	(0.008)	(0.012)
B. Effects by Relative Year			
Anticipatory Effects			
Event year - 2	-0.010	0.005	-0.011
	(0.007)	(0.008)	(0.012)
Post Treatment Effects			
Event year	0.083	0.005	0.017
	(0.007)	(0.009)	(0.014)
Event year + 1	0.147	0.018	0.022
	(0.008)	(0.010)	(0.015)
Event year + 2	0.192	0.034	0.054
	(0.010)	(0.012)	(0.018)
Controls	No	Yes	Yes
Observations	60,483	60,483	32,075

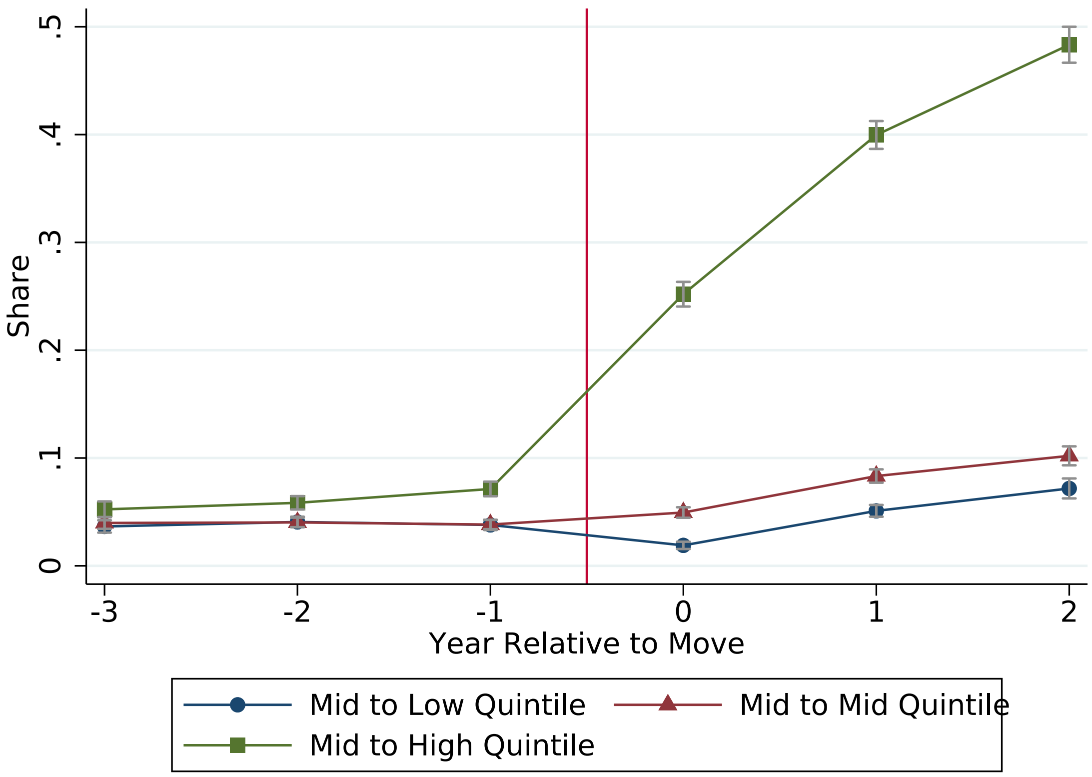
Notes: The table reports results from the event study regressions quantifying the experts channel detailed in Section (4.2.2). Outcome variable is the firm deduction decision and event year refers to the year of the incoming accountant. Event year - 1 is excluded and serves as the base category. Firm and year fixed effects are included throughout. Columns (1) and (2) refer to the full sample, and column (3) uses matching on observables. We control for average gross income, average age, share married, share female, share tertiary educated, firmsize, as well as industry and province dummies and dummies for the year of the accountant switch. Standard errors (in parentheses) are clustered at the firm level.b

Figure C.6: Coefficients on experience dummies



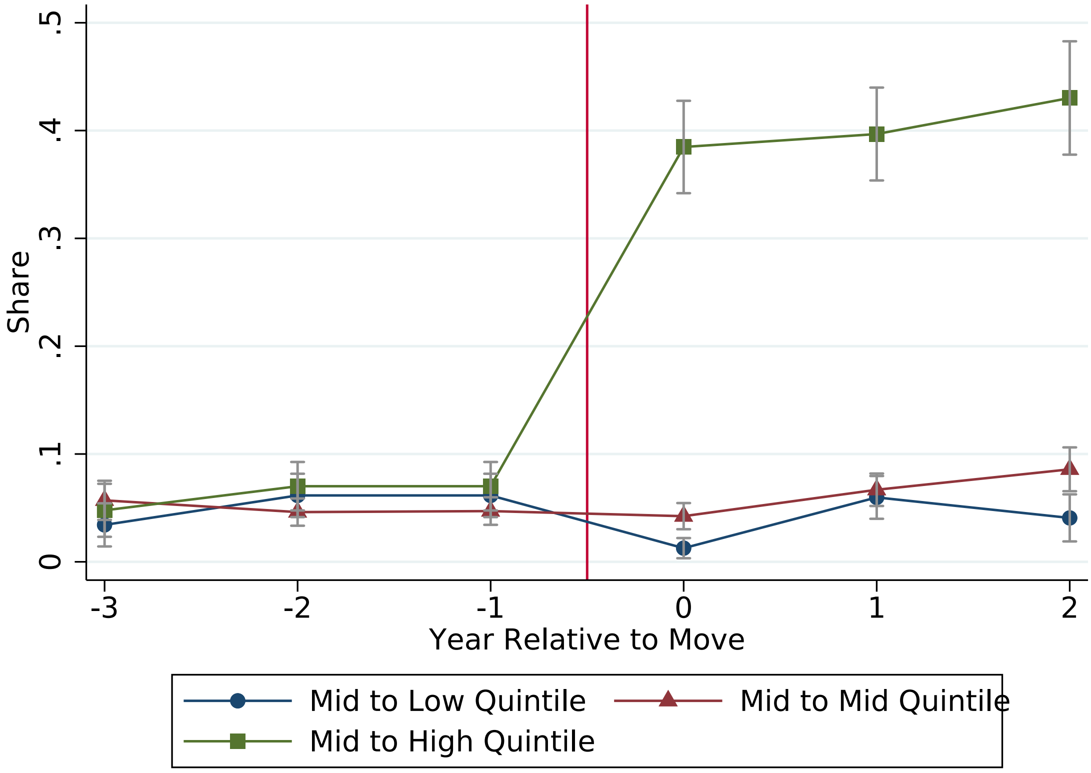
This figure depicts estimated coefficients from a linear regression of a deducting indicator on dummy variables for each year of experience in the formal sector. We control for individual fixed effects, income dynamics and a broad range of firm characteristics.

Figure C.7: Event Study Job Switchers



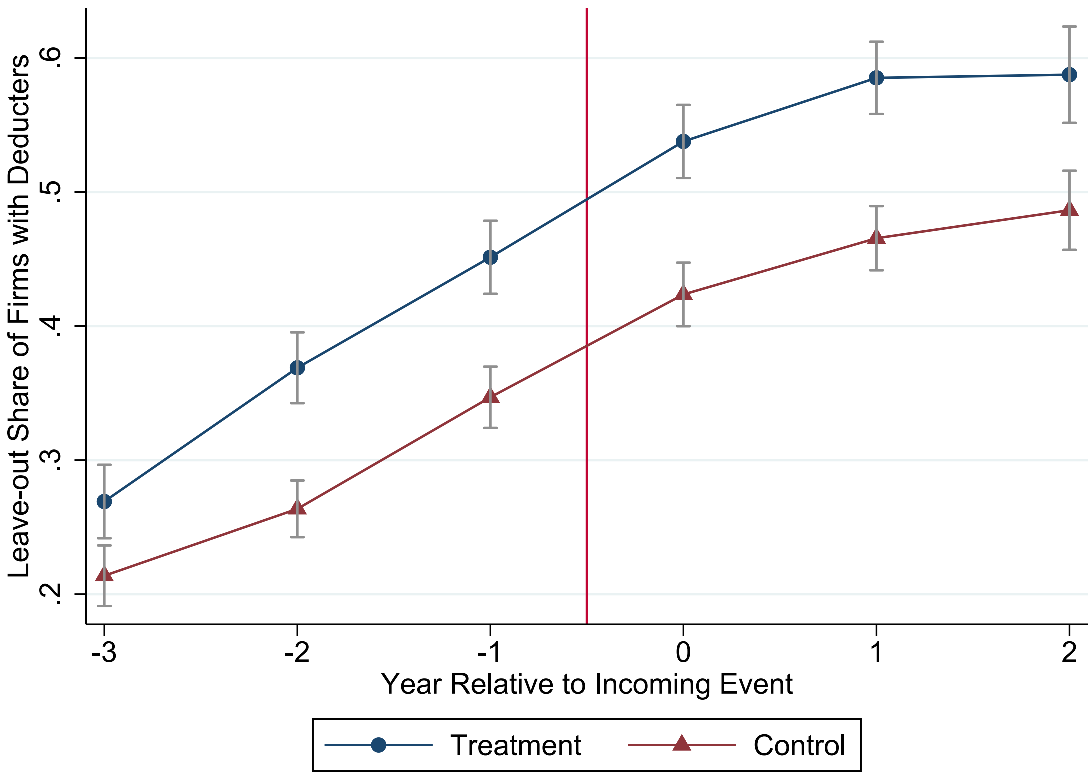
This figure shows an event study with deducting shares of job switchers around the time of the job transition. The vertical line indicates the time of the transition. We observe deducting among individuals who come from a firm in the medium quintile of the distribution of co-worker deducting shares and differentiate between those who switch to a firm in the bottom, medium, and top quintile.

Figure C.8: Event Study Job Switchers – Sample of Displaced Workers



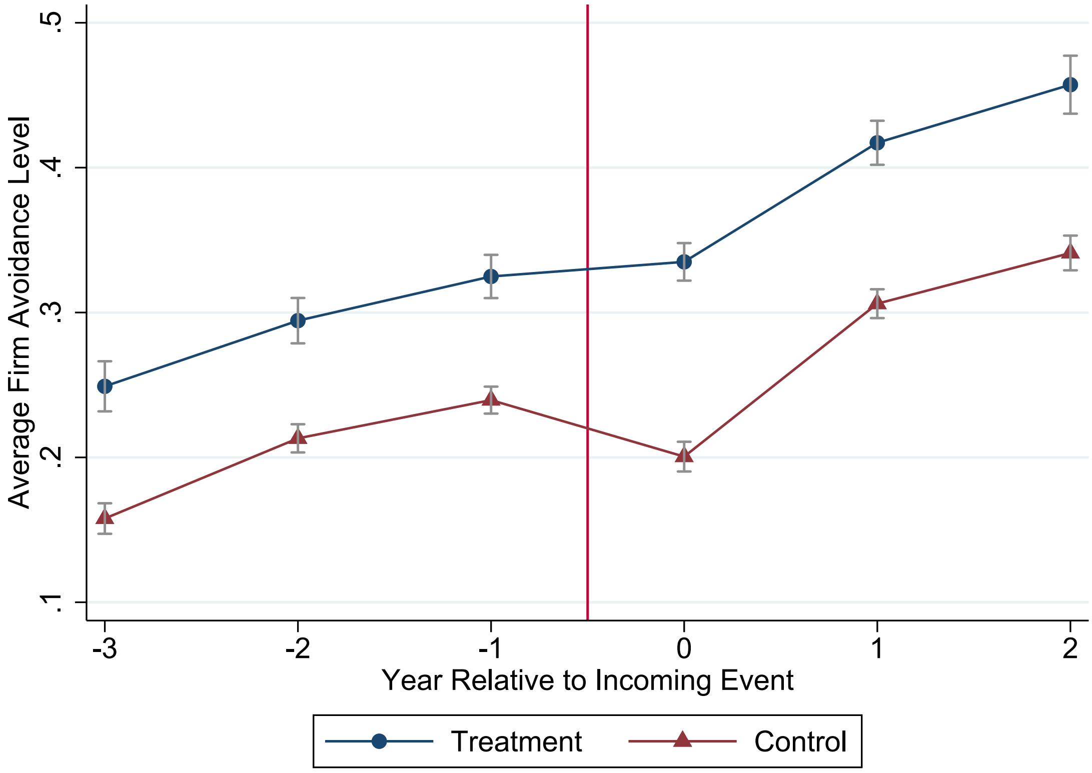
This figure shows an event study with deducting shares of job switchers around the time of the job transition in the subsample of workers who exogenously loose their job due to a firm closure.

Figure C.9: Peer Learning Event Study



This figure shows an event study on the firm level with the share of firms employing deducters around the hiring of a new co-worker (leaving out the new worker from the calculation). The vertical line denotes the arrival of the new worker. The treatment group is formed by firms that receive a new co-worker who was deducting in her previous firm while the control group is formed by firms with a new co-worker who was not deducting (despite being a potential deducter with gross income in the range above the kink).

Figure C.10: Experts Event Study



This figure shows an event study on the firm level with the average share of deducters around the entry of a new accountant into the firm. The vertical line denotes the arrival of the new accountant. The treatment group is formed by firms that receive an accountant who was previously working for a firm with deducters while the control group is formed by firms with a new accountant who was working for a firm without any deducters.