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Abstract

A recent Spanish tax reform granted regions the authority to set income tax rates, resulting in substantial tax differentials. We use individual-level information from Social Security records over a period of one decade. Conditional on moving, taxes have a significant effect on location choice. A one percent increase in the net of tax rate for a region relative to others increases the probability of moving to that region by 1.7 percentage points. Focusing on the stock of top-taxpayers, we estimate an elasticity of the number of top taxpayers with respect to net-of-tax rates of 0.85. Using this elasticity, a theoretical model implies that the mechanical increase in tax revenue due to higher tax rates is larger than the loss in tax revenue from the out-ow of migration.

JEL-Codes: H240, H310, H730, J610, R230.

Keywords: migration, taxes, mobility, rich, fiscal decentralization.

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High-income taxpayers may be literally "worth their weight in gold" to the government where they reside.[1] As a means of tax avoidance, individuals may move in response to tax differentials resulting from residence based local income taxes. Tax avoidance typically arises when taxable income can be shifted in a way that it becomes subject to a favorable tax treatment (Piketty and Saez 2013), and mobile taxpayers might simply relocate their tax residence to reduce their income tax burden. As a result of tax induced mobility by high-income taxpayers, governments may be unable to engage in progressive redistribution (Epple and Romer 1991; Feldstein and Wrobel 1998) and tax competition may intensify (Wildasin 2006). Despite the policy importance of analyzing taxation in an open economy setting, most studies have analyzed responses of taxable income (Feldstein 1999) although a recent literature on tax-induced mobility has emerged.

We provide evidence on migration resulting from a major Spanish tax reform and fiscal decentralization. In the early 2000s, all *Autonomous Communities* (regions or states) in Spain had the same top marginal tax rate. In 2011, Spanish regions began changing their top marginal tax rates in response to a federal reform that gave regions the authority to adjust rates and the corresponding tax brackets. In 2014, top marginal tax rates diverged across regions by as much as 4.5 percentage points. For an individual earning 300,000 Euros, this amounts to a tax differential of 10,000 Euros. These disparities in regional top tax rates led the popular press to dub low-tax regions such as Madrid as "tax havens" or one of several "paradises on Earth."

Research on migration requires linked data of individuals in the country of origin and destination, which is fairly complicated to obtain.[2] Exploiting sub-national variation is therefore an appealing alternative. However, personal income in most countries is taxed at the federal level and only a few countries tax personal income at the regional or

[1] The quoted phrase comes from Wildasin (2009), who writes: "at current prices ($900/oz.), an average adult male's weight-equivalent (190 lbs.) of gold is worth around $2.7 million. Under conservative assumptions about life expectancy and discount rate, the present value of taxes paid by very high income taxpayers can easily exceed this amount."

[2] Kleven *et al.* (2013) and Akcigit *et al.* (2016) are notable exceptions. They focus on selected subgroups of the population for which the authors have been able to assemble the information needed without access to individual income data linked across countries. Bakija and Slemrod (2004), Moretti and Wilson (2017) and Young *et al.* (2016) are also noteworthy state level examples, but as discussed below state level income taxation is not always residence based in the United States.

local level (i.e., United States, Canadian provinces were granted the authority to set their own bracket and rates in 2001 (Milligan and Smart 2016), Swedish municipalities, Italian regions and municipalities, Swiss cantons and localities). Given the expected mobility and avoidance responses, some of these countries only allow for small differentials across jurisdictions by limiting the tax-setting power of state and local governments. In countries with more substantial autonomy, regional personal income taxes have been implemented decades ago and large administrative data are not available for time periods before their implementation. Further, in the U.S., income taxes are often employment-based rather than residence-based, which means that for local moves, individuals may change jobs rather than residence to reduce taxes (Agrawal and Hoyt 2018).[3] The reform in Spain granted substantial autonomy to the regions on a purely residence-based tax system. Tax administration remains with the national authorities which facilitates access to individual micro-data that is available before and after the decentralization.

We use individual Social Security data for a sample of the population of Spain (excluding Navarre and Basque Country, which are not included in the data) from 2005 to 2014 to study the migration decisions of the rich in response to this unique fiscal decentralization. Our paper makes several contributions. First, we focus on all high income individuals rather than a select group of highly mobile individuals such as star scientists (Moretti and Wilson 2017; Akcigit *et al.* 2016), athletes (Kleven *et al.* 2013), or foreigners subject to preferential taxation (Kleven *et al.* 2014; Schmidheiny and Slotwinski 2015). In terms of the scope of the sample, Young *et al.* (2016) are the closest to our paper and utilize population level U.S. tax return data for all millionaires in the United State over a thirteen year period. Exploiting state-to-state migration of millionaires and an empirical design comparing millionaire populations at state borders, Young *et al.* (2016) concludes that although taxes matter, it is with only very small economic significance.[4] Second,

[3]In the United States, 5.3 million individual have an interstate commute. Approximately 75 million people live in metropolitan areas that cross state borders. Of these, approximately two-thirds live in MSAs that have an employment-based component to state and local income taxes.

[4]We make several contributions relative to Young *et al.* (2016). First, we study migration patterns of the rich (above 90,000 Euros) and not just the very rich (millionaires). We also study migration in a setting where regional taxes are purely residence-based; in the United States, taxes may have a residence and employment-based component. Finally, we show heterogeneous effects by industry and occupation.

we study migration using a random sample of population level administrative data for a complete panel of all regions in a country; Young *et al.* (2016) have similar data and a single state analysis includes Young and Varner (2011).[5] This administrative data provides us detailed information on industry and occupation that allows us to determine the generalizability of the prior literature focusing on specific occupations. We find significant effects of taxes on location choices, but an elasticity of the number of top taxpayers that is less than unity. We then contribute to the literature by using a theoretical model of revenues to simulate the implications of these elasticities for the fiscal authorities.

Discussion of taxing top incomes comes within the context of widening income inequality in many countries (Roine and Waldenström 2011). One discussed policy response to widening inequality is changing top tax rates. Bonhomme and Hospido (2017) document that earnings inequality in Spain declined from about 1995 to 2007, but that it has risen dramatically since 2007 and is back to its 1995 level. Studying mobility in Spain is especially important given the implications for redistributive tax policy. The mobility response – especially of high income taxpayers – is critical to understanding whether increasing progressivity at the regional level is a viable policy response to increasing inequality. Mobility in response to more progressive tax policy could threaten the ability to engage in redistribution given that the optimal degree of redistribution will decline as the mobility elasticity increases (Mirrlees 1982).

The paper proceeds as follows: we use a 4% random sample of administrative data that is released publicly to study tax-induced mobility. We use individual Social Security and tax administration data that contains information on each taxpayer's income that is not top coded. These data also contain information on the taxpayers declared location of residence in addition to certain characteristics reported to the Social Security administration. These data do not contain tax rates, so we write our own tax calculator from regional tax codes that simulates average and marginal tax rates back to 2005.

[5] Conway and Rork (2012) and Conway and Rork (2006) find no effect of state taxes on elderly migration. Brülhart and Parchet (2014) show that high-income retirees are relatively inelastic in response to estate taxes, but Eugster and Parchet (fc) provide evidence "consistent with top-income taxpayers moving from high-tax to low-tax municipalities" for local Swiss income taxes; Martínez (2016) finds estimates consistent with ours for Obwalden.

We first conduct an aggregated region pair analysis. We calculate for each year in our data, the stock of top-taxpayers for every region pair combination in Spain and construct the log ratio of the stocks across pairs; in addition, we calculate the net of tax rate differential between each of the region pairs. We then show that higher individual income taxes reduce the stock of top-taxpayers after accounting for destination fixed effects, origin fixed effects, and year fixed effects. The stock elasticity is approximately 0.85. Tax policy is not set randomly and any state-specific unobservable that is correlated with taxes and migration may threaten our results. To deal with this, we show that migration effects follow tax changes and do not pre-date them such that there are no pre-trends in the periods prior to the reform. We also show a placebo test: pre-reform population stock changes show no correlation with post-reform tax differential changes.

Then, we turn to an individual level analysis that studies whether individuals are more likely to select low-tax regions, conditional on moving. Our empirical choice model exploits individual variation in tax rates across the fifteen Spanish regions; given we exploit person-specific tax rates, our model allows us to account for region by year fixed effects and individual characteristics that are allowed to vary by region in order to capture counterfactual wages in alternative regions. This approach has the advantage of allowing us to account for fixed characteristics of the mover that are constant across alternative regions, any sorting based on characteristics, as well as for other policy changes that affect all individuals in the top of the income distribution. A one percent increase in the net of tax rate for a region relative to others increases the probability of moving to that region by 1.7 percentage points. Although many things may matter for decisions on where to move, taxes appear to be important. These estimates suggest that the 0.75 percentage point average tax rate differential between Madrid and Cataluña in 2013 increases the probability of moving to Madrid by 2.25 percentage points. This analysis is summarized in figure 1, which shows no correlation in the pre-reform period, but a strong correlation in the post-reform period for location choices and taxes.

We then exploit the administrative data on occupation and industry to show that taxes play a stronger role for certain occupations and industries. Testing for heterogeneity across occupation and industry helps to inform the recent policy debate on the efficiency of tax schemes for top earners in specific occupations. Several OECD countries have preferential tax schemes for foreigners in high-income occupations.[6] By focusing on the heterogeneity by occupation and industry, we can shed light on the efficiency of these tax schemes. First, we replicate the result in the prior literature for scientists and find that those in the "professional/scientific" and "health" industry have large and significant migration effects; entertainers including athletes have insignificant effects, likely due to sample size. Then, we look at other occupations and industries to determine if the estimates for the occupations studied in the prior literature generalize. Our results indicate that self-employed (a self-employed individual will only have income in the data for formal contracts with firms registered with the Social Security administration) and "higher-ability" occupations are more sensitive to taxes. Our industry-level data demonstrates substantial heterogeneity with the largest effects emerging in finance, real estate, and information, in addition to the professional/scientific industries studied previously.

Our analysis comes with a caveat: our data do not allow us to disentangle a real move from a fraudulent move where the taxpayer changes residence to a second home without actually changing where they spend the majority of the tax year. In so much as this is possible, the presence of such evasion implies that mobility includes both real responses as well as tax evasion responses. From a tax revenue perspective, it does not matter if the move is a real response or simple misreporting; from a labor supply perspective, real moves may be more important.

As noted in Saez *et al.* (2012), absent both classic and fiscal externalities, the elasticity of taxable income (ETI) suggests that the revenue maximizing tax rate on top incomes may be as high as 80% with a broad income tax base. However, changes resulting from mobility across regions are not generally captured in these estimates and therefore understanding mobility has important implications for understanding the optimal top

[6] For example, Denmark has income tax exceptions for foreign scientists, Korea has exceptions for high-tech fields, Poland has exceptions for workers engaged in artistic, scientific, sport or expert activities, and Switzerland has exceptions for managers and specialists. In the United States, many states have aggressively passed "jock taxes" that target professional athletes, which enforce tax collections based on the number of duty days worked in a state.

income tax rate. In order to interpret the elasticities that we estimate, we simulate a revenue maximization model incorporating migration. The model suggests that the effect of changes in taxes on revenue can be decomposed into a mechanical (tax rate) effect from higher taxes, a behavioral effect from changes in taxable income, and a migration effect. The last effect depends on the stock elasticity of migration. Using our stock elasticities, we find the mechanical effect dominates the other effects for all regions in Spain, which has important implications for how much additional revenue a region can raise [lose] by raising [lowering] its top tax rates. For the region of Madrid, its lower rate relative to the central government tax rate in 2014 results in revenue falling by 50 million Euro due to the mechanical effect of the lower tax rate. Using our mobility estimates, migration effects only contribute 9 million Euro more in revenue. For behavioral responses to entirely offset the mechanical effect net of mobility effects, the elasticity of taxable income would need to be 1.40, which is well above reasonable estimates of it. We conclude that, at least in the short-run, migration does not pose a large threat to redistributive taxation.

1 Institutional Details

Spain consists of 17 autonomous communities (in Spanish: *comunidades autónomas*) which are comparable to states or regions in other countries. The autonomous communities are governed according to the Spanish constitution. Furthermore, the individual competences which each region assumes are regulated by a region specific organic law, known as Statute of Autonomy.[7] Important for our purpose is that taxes are due at the place of residence (*residencia habitual*), which is declared in the local municipality of residence. Since 1994, the regions receive a share of the Personal Income Tax (*Impuesto sobre la Renta de las Personas Físicas*) as part of their revenues, but it was only in 1997 that partial autonomy over marginal tax rates was delegated to the regions (see Durán and Esteller 2005). Initial regional autonomy was quite limited as regional level marginal tax rates applied only to 15% of the tax base and thus autonomous communities had little interest in changing marginal tax rates. Instead, they focused on setting tax credits, mostly for housing and renting as well as some personal circumstances such as ascendants

[7]In general, the top spending categories by regions in Spain are education and health. These are services that are disproportionately consumed by lower-income groups.

and decedents.[8] In 2007, following some reforms, the regional-level individual tax rates still had to complement the common tax brackets set by the central level, but they were applied to a larger share (35%) of their residents tax base.[9] Therefore, in 2007, Madrid was the first autonomous community which changed marginal tax rates, followed by La Rioja and Valencia in 2008. These regions implemented top marginal tax rates which were slightly lower (less than 0.1 percentage point) than the federal tax schedule. Murcia followed in 2009, but returned to the common federal scheme thereafter. These initial reforms resulted in very small differences in taxes across regions.

Another major wave of decentralization reforms followed this process in 2009 (last laws approved in July 2010) but regions could not exercise their new rights until 2011. Regions could now keep the revenues collected from half of the entire tax base in their territory. In addition, regions were also given the right to introduce new tax brackets on top of those implemented by the central government. In 2011, with both the ability to construct new brackets and marginal tax rates in hand along with added incentives to retain more of the tax revenue, several regions increased marginal tax rates substantially, while the ones which decreased them previously lowered their rates (Bosch 2010).[10] Another reason for the immediate reaction of regional governments was that in 2011, the federal government raised marginal tax rates substantially and regions used this event to increase simultaneously their own tax rates, or decrease them to counteract the federal increase. In subsequent years, some further changes in regional top tax brackets were implemented, but the pattern of high versus low-tax regions as of 2011 generally persists to the end of our sample in 2014.[11]

[8] Durán and Esteller (2006) show that those tax credits lower predominantly the effective tax burden for the poor, as many of them fade out with income. A prominent example are tax credits given to young individuals renting a flat in various regions. However, only young and low income individuals are eligible (for example below 35 years of age and 19,000 Euros in Extremadura, and 32 years and 20,000 in Cataluña). Madrid allows for a small deduction of school books for families with a tax base below 30,000 Euros, to give a further example of these types of deductions.

[9] c.f. Ley 35/2006, de 28 de noviembre, del Impuesto sobre la Renta de las Personas Físicas y de modificación parcial de las leyes de los Impuestos sobre Sociedades, sobre la Renta de no Residentes y sobre el Patrimonio.

[10] In all subsequent discussion referring to the tax reform, we mean this 2011 reform. Any differences prior to this reform were trivial – for top earners – in comparison.

[11] A confounding factor could be the re-introduction of the wealth tax at the end of 2011. The decision was taken at the end of 2011, such that an immediate response in that year – and even one in 2012 is unlikely to happen. Further, the tax has been introduced as an explicitly temporary measure to reduce

The regional tax changes are salient to top taxpayers. Tax forms compute an individual's average regional and federal tax liability separately so that the individual sees both average tax rates.[12] When filing taxes in April, taxpayers are asked to state their place of residence. A change of their address can be done online at the same page where individuals submit their tax declaration and becomes effective immediately.[13]

In Spain, the personal income tax is a dual tax which separates the income tax base and the capital income tax base. The reform *only* allowed regions to alter marginal tax rates of the labor income tax base, while the capital income tax base remained taxed under a common tax schedule. Given that we will use Social Security data to study migration, pure rentiers (individuals with capital income only) will be absent from the data. However, given that these rentiers face a common federal tax rate on capital income, the decentralization of the labor income tax base is irreverent for these individuals. The reform did not affect corporate taxes, so we do not have to worry about any correlation with corporate taxes, which remain the authority of the federal government.

1.1 Descriptive Figures of the Reforms

In 2010, all regions in our data set have tax rates that are within 0.10 percentage points of each other. But, by 2014, substantial spatial variation had emerged. All tax rates increased over time in levels – although some decreased relative to the federal rate, which was changing over time. Figure 2 shows the changes for all regions and for all brackets. In order to ease interpretation, we show the tax changes relative to what the tax rate would be if the region had simply adopted the federal tax rates in that year. Relative to this standard, some regions decreased their tax rates while others increased their tax rates. Immediately following the reform, top tax rates diverged by 5 percentage points. This pattern persisted with some changes to lower bracket tax rates.

Given that many tax brackets change (and not just the top marginal tax brackets),

fiscal problems during the Great Recession. Not until the end of 2012 did the government announced that the tax will also be applied in the following year, again without establishing the tax permanently.

[12]Although individuals know their average tax rate in the region of residence, it is unlikely they would know the exact average tax rate in all of the alternative regions within Spain. For this reason, high-income taxpayers may use the top marginal tax rate as a proxy for their expected tax liabilities in other regions. Gideon (2017) shows that many people think that all income is taxed at the marginal tax rate.

[13]We do not observe the location declared on the return. However, tax inspectors afterwards might double check any change of the fiscal residence with the data from the local register which we observe.

we need to justify our focus on the top of the income distribution. The red vertical line in figure 2 shows the cutoff for the top 1% of income. Notice that the top 1% – incomes above 90,000 Euro approximately — experienced the largest changes in tax rates across regions. The tax differences for individuals even in the top 2 to 5% were relatively small across regions – this is because even if marginal tax rates differed across regions, average tax rates were relatively similar.

1.2 Who Changes By Larger Amounts?

Regions that raise their tax rates by the largest amounts might be those regions where the mobility of top earners has been declining or where the stock of top earners is large or small. Regions had little information about how individuals would respond to tax changes given the immediate decentralization and tax changes following the reform. Simple correlations in appendix A.1 show that characteristics of the region related to the top 1% seem to have small effects on the tax changes. Larger correlates with the tax changes are political associations, debt, and income conditions.

Although the equilibrium tax rates may be a result of a rather arbitrary political process, this is not to say that the resulting equilibrium tax rates are as good as random. In particular, the resulting tax rates following the policy decentralization may be a function of unobservable characteristics. While this is not something that we can rule out entirely, we provide evidence that this does not appear to be the case. First, we do not find pre-trends in the populations of the regions; changes in the population stocks occur after the tax changes. Second, we show that post-reform tax rate changes do not predict pre-reform populations or migration flows suggesting that regions do not set taxes based on pre-reform characteristics. Of course, other unobservable changes in state policy or state shocks may exist. While we cannot rule this possibility out with aggregate data, we then turn to individual level data where we can control for state by year shocks.

2 Description of Data

We use panel data from 2005-2014 from Spain's Continuous Sample of Employment Histories (*Muestra Continua de Vidas Laborales*, MCVL). The data is provided by the Ministry of Employment and Social Security *(Ministerio de Empleo y Seguridad Social)*. This administrative data matches individual microdata from social security records with data from the tax administration (*Agencia Tributaria,* AEAT), and official population register data (*Padrón Continuo*) from the Spanish National Statistical Office (INE).[14] The Social Security administration publicly releases an approximately 4% non-stratified random sample (over 1 million observations each year) of the population of individuals which had any relationship with Spain's Social Security system in a given year due to work, receiving unemployment benefits, or receiving a pension. These data have been previously in applied work on labor and urban economics (Bonhomme and Hospido 2017; De la Roca and Puga 2017). Individuals from Navarre and the Basque Country do not appear in the data because these regions operate independent fiscal systems.[15] If an individual is in the data, they remain in the data as long as they have contact with the Social Security ministry, but new observations enter each year so that it remains representative. Self-employed individuals that make contact with the Social Security system do appear in our data, however, we only observe income for them if they have a relationship with a registered firm, as the firm remits taxes on their behalf. Self-employed individuals that do not have contracts with firms do not appear in the data; however, we believe that at the very top of the income distribution most self-employed individuals provide services to firms such that they will be covered in our sample. Nonetheless, even for self-employed individuals with some contracts with firms, we may mismeasure their true income.

One key is that from 2005 to 2014, the Social Security data are matched to income from tax data. These income tax data are valuable because they are not subject to censoring; Social Security contributions are censored and do not contain some portions of income that are important for high income tax payers. Given we will focus on top income taxpayers it is important we have income data that is not censored and contains all sources of income.[16] The observational unit of the raw data is based on each contact

[14]Residence data in the Social Security data are less controversial; the tax return data often reports the location of work. Social Security data contains residence information based off local registers.

[15]We exclude the individuals living there from our analysis. We treat people moving to those two regions as people leaving the sample for any other reason (moving abroad, etc.). However, we do include people moving from those two regions to another region in Spain as we observe their income in the new destination and know the origin from the social security database. We furthermore exclude Ceuta and Melilla, two autonomous cities (not autonomous communities) on continental Africa.

[16]As noted in Bonhomme and Hospido (2017): "... social security contributions exclude extra hours,

(for example, job) an individual had within a given year with Social Security. We define the main work affiliation in each year as the one which was active for the longest time span since starting work. We aggregate this data at the individual level to obtain a panel data set which sums all individual income sources in a given year for a given tax payer.[17]

We define a change of location if an individual changed his or her residence between t and $t-1$.[18] Residence data of the current year is updated using the residence of April in $t+1$, which ensures that this period overlaps with the tax year as tax declarations are due in April to June. As an example, an individual would be characterized as a mover in 2012 if he was living in a different region between April 2012 and April 2013 compared to his residence between April of 2011 and April 2012. In this way, his 2012 income is the relevant one for tax purposed in the region he moved to.[19] While residence information is available at much smaller spatial units, in this paper, we will define a "mover" as an individual that relocates *across* (not within) regions. One reason for this is that we only observe municipality codes for individuals living in sufficiently large cities, which means that many within region moves remain unobserved to us.

We construct taxes using the sum of all reported income by different employers within each year which is subject to the personal income tax (labor income, reported self-employed income, and income in-kind). Given this information and other attributes, we simulate average and marginal tax rates for each individual in each year for each region

travel and other expenses, and dismissal compensations. These differences seem more relevant for high skilled workers as the correlation in levels between contributions and taxable labor income is lower for the first group [high-skilled] (70%) than for the others (over 85%)." Given our focus on high-income taxpayers we use the tax income data.

[17]Only a small fraction of the sample are reported as "married" with a substantial fraction declaring "other." Because of this, two individuals may move in our data when they are a common household. Our results are robust to using only county pairs featuring only a single mover in a given year.

[18]The transition matrix of movers in the pre- and post-reform period are given in appendix A.2.

[19]Registration is mandatory within three month and municipalities have an incentive to register citizens because they receive transfers allocated on a per capita base (Foremny *et al.* 2017). An alternative location variable which is available in this data-set are the region the firm provides when they remit taxes for the individual. This does not have any legal effect on tax declarations (it is not the state the individual files their taxes in), but rather corresponds to the address on file with the employer reporting the contract. We observe 57% of movers have firms reporting the same state from the registrar data. Adding the observations for which the province declared by a firm coincides with the residential province before moving increases the share to 96%. This indicates that there is rather a lag of updating the firm database than the official register, which is not surprising given that the address communicated to the firm does not have any legal (or even tax) consequences. Thus, the registrar data is preferred. However, we reestimate our individual model excluding observations where the firms report a different address than the location before or after the move in the registrar data; results remain similar.

using the information in the tax code provided by official documents.[20] This simulation takes into account the variation of marginal tax rates, their brackets, and basic deductions and tax credits for ascendants, decedents, and disabilities. We do not take into account any further region specific deductions or tax credits. However, given that we focus on high income individuals, this would almost never affect the marginal tax rate and the average tax rate only to a negligible amount as those omitted policies are targeted to low income individuals.[21] We use the tax calculator to simulate the tax rate in the region of residence and the tax rates in all counterfactual alternative regions.

Summary statistics of our data are given in appendix A.4. Unique to our setting is detailed data on occupation and industry. The appendix also shows descriptives concerning the top occupations and industries of movers in the top 1%.

3 Aggregate Analysis

3.1 Theory of Population Stocks

For simplicity, consider a two region economy where $r = o, d$ indexes the two regions, which we call origin and destination for simplicity.[22] The utility of top income individuals living in region r in period t is given by:

$$V_{r,t} = \alpha u(c_{r,t}) + \pi v(g_{r,t}) + \mu_r - \gamma \rho(N_{r,t}) \tag{1}$$

where $c_{r,t}$ is private consumption of the individual, $g_{r,t}$ is public services consumption, μ_r is the value of other amenities that are specific to living in the region. The function ρ is a disutility that depends on population. The $\rho(N_{r,t})$ function allows us to indirectly bring in housing markets into the problem: a region becomes less attractive, the larger is its population perhaps because housing prices increase. In particular, fewer people in a region mean the cost of housing will be lower which raises utility relative to a region

[20]We use the tax laws to write a tax calculator for Spain similar in spirit to TAXSIM. Details of the calculator are in appendix A.3.

[21]Omissions from the tax calculator are common to all calculators. Even NBER's TAXSIM does not present a complete set of tax rules for all states and years. Measurement error is addressed via IV.

[22]For lack of a better term, we refer to one region d as the destination and the other o as the origin. Given these are stocks and not flows there is no origin or destination per se. Nonetheless, this verbiage will help us talk about the model without having to refer to arbitrary region pairs.

with more people and higher housing costs.[23] In particular, this congestion cost it is an alternative mechanism to get to a spatial equilibrium even without formally modeling housing price adjustments. Following the standard in the literature, we assume that the separable functions u, v, and ρ each take on the log functional form.

Each individual supplies a fixed unit of labor so that given the nature of the problem, an agent consumes all after-tax income: $c_{r,t} = (1 - \tau_{r,t})w_{r,t}$ where $\tau_{r,t}$ is the tax rate on wages $w_{r,t}$. In practice, $\tau_{r,t}$ is not a single rate but rather is the average tax rate on wages. If the tax system exhibits any progressivity, then $\tau_{r,t}$ will be a function of $w_{r,t}$; thus, a progressive tax system would require estimation to use an average tax rate. To see this, a progressive tax system would be given by the tax function $T(w_{r,t})$ and so consumption would be $c_{r,t} = w_{r,t} - T(w_{r,t}) = (1 - atr_{r,t})w_{r,t}$ and the subsequent derivation follows using an average tax rate.

To close the model, we assume a simple model of production. Production in any given region is given by $f(N_{r,t})$ and satisfies the standard properties $f_{N_{r,t}} > 0$ and $f_{N_{r,t}} < 0$; the price of output is normalized to one Euro. With mobility, the equilibrium in the labor market requires the wage rate equal the marginal product of labor $w_{r,t} = f_{N_{r,t}}(N_{r,t})$. Assuming that production is given by $A_r N_{r,t}^{\theta} \bar{K}_r^{\vartheta}$ where A_r are fixed productive amenities in the region and $\bar{K}_r$ is the land/capital stock that is fixed in the short run.[24] Then we have in each r that $w_{r,t} = \frac{A_r \bar{K}_r^{\vartheta}}{N_{r,t}^{\theta}}$.

A locational equilibrium requires for all $r = o, d$ that $V_{o,t} = V_{d,t} = \overline{V}$. Setting $V_{o,t} = V_{d,t}$, taking logs of the equilibrium wage equation and substituting implies

$$ln(\frac{N_{d,t}}{N_{o,t}}) = \frac{1}{\theta + \frac{\gamma}{\alpha}} ln\left(\frac{1-\tau_{d,t}}{1-\tau_{o,t}}\right) + \frac{\pi}{\alpha(\theta + \frac{\gamma}{\alpha})} ln\left(\frac{g_{d,t}}{g_{o,t}}\right) + \zeta_d - \zeta_o \tag{2}$$

where ζ_o and ζ_d are defined to include the fixed productive amenities, fixed capital resources and consumption amenities across regions defined above. The above equation

[23] To see the idea of this function, consider an example. Suppose both regions were ex ante identical and private and public consumption are the same in both regions. Then an individual who moves from region o to d will, all else equal, realize a lower level of utility in region d because after the move $N_{d,t} > N_{o,t}$. For this reason, we think this is an attachment to home function.

[24] Of course, we can generalize the model to contain endogenous capital or housing for individuals.

characterizes the equilibrium in the model.[25] Notice that the endogenous adjustment of wages can be obtained as $\frac{dln(w_{r,t})}{dln(1-\tau_{r,t})} = \frac{dln(N_{r,t})}{dln(1-\tau_{r,t})} \times \frac{dln(w_{r,t})}{dln(N_{r,t})} = -\theta\frac{1}{\theta+\frac{\gamma}{\alpha}}$, which allows for the possibility of less than full capitalization of wages. This expression clearly highlights the role of the congestion cost and the parameter γ.

3.2 Methods

We estimate the pairwise *equilibrium condition* derived in (2). Denote the net of tax rate with respect to the average tax rate by $1 - atr_{d,t}$ $[1 - atr_{o,t}]$ in the destination [origin] region. We calculate the average tax rate for a representative taxpayer in the top 1% of the income distribution. We estimate for the working-age population:

$$ln(\frac{N_{d,t}}{N_{o,t}}) = \beta[ln(1-atr_{d,t}) - ln(1-atr_{o,t})] + \zeta_d + \zeta_o + \zeta_t + \delta ln\left(\frac{g_{d,t}}{g_{o,t}}\right) + X_{do,t}\phi + \varepsilon_{do,t} \quad (3)$$

where β captures the effect of taxes on population stocks, which is a function of the structural parameters in (2).[26] As suggested by theory, we include origin fixed effects that capture amenities (both for households and firms) in the region of origin and destination fixed effects that capture such amenities in the destination region. These fixed effects also capture any time invariant policies of the regions over our sample. Time fixed effects are included in the model to capture any aggregate shocks. As suggested in (2), we control for region-level spending changes across the regions. These spending controls are designed to capture the effect of any changes in services that may make a region more attractive following a tax change. In particular, we control for differentials on basic public services, social protection programs, public programs, general spending, and transportation infrastructure. In some specifications we include a vector $X_{do,t}$, where we control for time varying, region-pair specific shocks including economic shocks, demographic shocks, and regional amenities. These controls help facilitate identification given that the tax changes are not likely random. Given the set of fixed effects and covariates,

[25] The model can be derived without the ρ function using a fixed cost of moving by lowering utility in the destination region by that fixed cost. In this case, the only difference is the degree of capitalization into wages. Our model delivers partial capitalization into wages. The fixed cost delivers full capitalization.

[26] Note, as discussed previously, there were some very small tax differentials (around 0.10 percentage points) that existed prior to 2011. For ease of interpretation, we set these differentials to zero prior to 2011. If we include them, the coefficient is almost unchanged.

identification requires that, absent tax changes, region-pair stocks are fixed over time.

Notice (2) leads to a structural interpretation of the estimated coefficient in the locational equilibrium: β is the effect of tax rate changes including their indirect effects through changes in the regional wages, i.e. the effect taking all fixed regional characteristics (amenities) and public services as given except for tax rates *and* wages.[27] Given the structural interpretation of β, the endogenous capitalization into wages does not pose a threat to identification, but other unobservable wage shocks that are correlated with tax changes would be problematic. To deal with other shocks to wages, we control for time-varying regional economic conditions in $X_{do,t}$.

Theory implies to estimate the equilibrium condition using the ratios of populations and taxes rather than the level of the region's own population. In particular, this pairwise ratio is useful because we have a small number of regions, which implies the number of people in a given region depends on the entire vector of net of tax rates in all of the regions. Thus, tax changes in region $r' \neq r$ will have a *non*-zero effect on $N_{r,t}$. This is a purpose of estimating the stocks in pairwise ratios. Of course, this pairwise estimation complicates treatment of the standard errors and interpretation of β. We cluster the standard errors three ways to account for correlation over time within region-pairs and to account for the correlation of errors within both origin and destination by year pairs.

Estimating the location equilibrium condition in ratios influences the interpretation of β. Given we allow the tax rate of a given region to influence the population of other regions, the estimating equation delivers the elasticity of the ratios, $N_{d,t}/N_{o,t}$. Differentiating (3) with respect to the net of tax rate in region d, yields:

$$\beta = \frac{\mathrm{d}ln(N_{d,t})}{\mathrm{d}ln(1 - atr_{d,t})} - \frac{\mathrm{d}ln(N_{o,t})}{\mathrm{d}ln(1 - atr_{d,t})} \equiv \eta - \mu \tag{4}$$

where η is the stock elasticity of the population in region d with respect to its own net-of-tax rate and μ is the cross-elasticity of region o's population with respect to region d's

[27] A similar estimating can also be derived from a stochastic McFadden-type location choice model without assuming spatial equilibrium through wages. But, then (endogenous) wages would need to be controlled for in its estimation. This is an important contribution of the theory because dealing with endogenous wages would be difficult.

net-of tax rate. Given $\eta > 0$ and $\mu < 0$ are opposite signed, we can conclude that our estimate of β will over-estimate the elasticity of the stock of a given region. However, as the number of regions becomes large, then $\mu \to 0$. In our setting, with fifteen regions, we expect μ to be non-zero, but relatively close to zero and thus β acts as a reasonable approximation to the stock elasticity. We verify this is true by estimating the model in levels, which assumes a large number of regions and zero cross-price effects.

Some notes concerning the empirical model are in order. First, in our baseline specifications, we utilize net-of-average tax rates. To construct the average tax rate, following Moretti and Wilson (2017), we simulate taxes in all years and regions for a representative taxpayer in the top 1% holding fixed (across regions and time) income and any inputs to our tax calculator so that variation in the rate is only due to statutory changes. As noted above, the use of the average tax rate is theoretically grounded. However, some of the prior literature has presented results using the top marginal tax rate (Kleven *et al.* 2013; Akcigit *et al.* 2016) as a good approximation of the average tax rate. We also present results using the top marginal tax rate in each region, but note it is not a good approximation to the average tax rate in our setting. The top marginal tax rate will be correlated with the average tax rate because regions that raised the top tax rate were also generally regions that raised rates in lower income brackets (see figure 2). Although our preferred specification uses the (theoretically grounded) average tax rate, the top marginal tax rate may be very salient when determining the tax liability of the alternative regions; although individuals know the average tax rate in their region, they are unlikely to be able to calculate this across all of the alternative regions.

We estimate a stock model rather than a flow model. First, the stock elasticity is the parameter of interest in the revenue simulations we will conduct. Second, estimation in the flow model raises selection concerns because we do not observe migration between some regions due to our 4% sample and because a flow model would miss international migration and to the Basque country and Navarre; the stock model will not. Finally, a flow model would rely on a model where utility of being in any location is always conditional on where individuals are located to start with in period t; then identification requires region-pair migration flows are fixed over time rather than the stocks. Appendix A.5 discusses this in detail. The stock model avoids all of these issues and in our opinion, provides a more accurate measure of all tax-induced migration. Limitations of the aggregate analysis resulting from non-random setting of tax rates are addressed in section 4 where we control for time varying region-specific shocks.

3.3 Results

Given the simple panel data setting, we present our baseline results visually. To do this, we regress the stock ratio on the fixed effects and controls and then predict the residuals. We then regress the net of average tax rate variable on the fixed effects and predict the residuals. We then bin the residuals into equally sized bins and fit a line of best fit through these data. Figure 3 shows the baseline results; the upper two panels present the results using the average tax rate while the lower panel shows the marginal tax rate. We present all results with and without covariates to see if our identifying assumption is reasonable. Because all tax variables are in terms of the net of tax rate, when individuals keep more on the Euro in region d relative to region o, they are more likely to move to (or stay in) region d and the stock increases in d relative to o. As the net of tax differential increases, we see that it is consistent with $\beta > 0$. The addition of covariates does not meaningfully change the slope, but does reduce the noise. The bottom panel shows the regression using the marginal tax rate. Although the vertical axis is identical to the upper panel, the horizontal axis is more disperse because differences in top marginal tax rates are larger than average tax rates. Thus, the slope of the line of best fit remains positive but is flatter because a one percent change in the net of (marginal) tax rate will have a smaller effect on changing tax liability.

We present point estimates of β and standard errors for the aggregate analysis in table 1. If we assume that the cross-elasticity is small, the specification without controls suggests the stock elasticity is approximately 0.92. Our estimates of the elasticity are stable and are not statistically different with or without other covariates. With covariates, it rises just above unity. This estimate of the elasticity is higher than the estimates in Moretti and Wilson (2017), who obtain a stock elasticity of 0.45; Akcigit *et al.* (2016)

estimate an elasticity of 1 for foreign star scientists. It is larger than Young *et al.* (2016) who find very small effects. The elasticity with respect to the top marginal net-of-tax rate is 0.65; the smaller elasticity makes intuitive sense because a change in the top marginal tax rate only affects some taxpayers.

A concern with this model is that we may overestimate the stock elasticity resulting from migration because of taxable income responses. In particular, we might worry that in regions lowering their tax rates, taxable income may rise resulting in more people moving into the top 1% of the income distribution in that region. To address this concern, we implement several robustness checks. In table 1 we show the results are robust to controlling for the (endogenous) ratio of taxable income reported by the top 1% in the region pairs. Second, and more preferably, we also adjust the population stocks accounting for movement within the income distribution. Let $\Delta_{r,t}$ be the number of people who move in/out of the top percentile of the income distribution in region r. This number is calculated as the number of people who are in the top 1% this year but were not in it last year minus the number of people who were in the top 1% last year but are not this year. Then we calculate an adjusted stock ratio using $\widetilde{N_{r,t}} = N_{r,t} - \Delta_{r,t}$. We then run all specifications using $ln(\widetilde{N_{d,t}}/\widetilde{N_{o,t}})$ as the dependent variable so that we are exploiting variation in the stock of people in the top 1% adjusted for any yearly churn in the income distribution. After doing this, with covariates, we estimate an elasticity of 0.88, which falls slightly suggesting our prior estimates may capture some taxable income responses.[28] We also estimate a taxable income elasticity directly by regressing the share of total earned income (working age individuals, excluding pensions and unemployment benefits) in a region earned by the one percent on the net of tax rate, region and year fixed effects. This regression estimates a small insignificant elasticity suggesting we are identifying mobility effects in our stock analysis. Appendix A.6 shows the small taxable

[28]Again, assuming the cross-elasticity is small, to interpret the economic magnitude of the 0.88 elasticity in column 4, the average region in our sample has a stock of 565 taxpayers in the top 1% of the income distribution (recall we have 4% random sample, so multiplying by 25 yields population level estimates). The average net of tax rate (federal plus state) implies that a 1% change in the net of tax rate results in a 0.54 percentage point change. The absolute value of the net of tax differential between regions is on average 1.2 percentage points or 2 times a 1% change in regional tax rates. Combined with our elasticity, this implies a change in the stock of top taxpayers by 11 taxpayers.

income response. This is consistent with Rubolino and Waldenström (2017), which estimates a taxable income elasticity for the top percentile in Spain of 0.05. The results of these exercises suggest that we are not identifying taxable income responses. However, to further address this issue, we will subsequently turn to an individual analysis where taxable income responses will not be a concern for identification.

We also test for a heterogeneous effect of the tax reform on other lower income groups. In particular, we consider whether these lower income groups respond to the average tax rate for top income taxpayers. In figure 4 we present (using the same scale as the upper panel in the prior figure) results for the top 5% (excluding the top 1%) and the top 10% to 5% of the income distribution. A mildly positive pattern emerges in response to the average tax rate differentials for the top 5% and the slope is declining as income declines. So, what makes lower income households less responsive to the tax differentials? They have smaller tax rate differentials due to progressivity and the top 1% average tax rates may not be relevant for them unless they anticipate income growth, they may care relatively less about tax rates and more about public services because of non-homothetic preferences, or they may have lower moving probabilities because of relatively higher moving costs and less job opportunities. Thus, these results should be interpreted as an analysis of heterogeneity rather than a placebo test given that the differences along these dimensions cannot be ruled out.

Given identification is based on a large reform, we wish to show a break in the patterns following the 2011 reform. For each region pair d and o, if the net of tax differential increases in region d relative to region o, we classify that pair as one where the net of tax rate increases. The left panel in figure 5 shows the raw averages of the stock ratio for pairs where the region d gets to keep more income (taxes fall) relative to region o. For these observations, the stock ratio increases following the reform and remains higher. To do this formally, we implement an event study approach by estimating

$$ln(\frac{N_{d,t}}{N_{o,t}}) = \overline{ln(\frac{1-atr_d}{1-atr_o})}[\sum_{y=-6}^{-2} \pi_y 1(t-t^* = y) + \sum_{y=0}^{3} \gamma_y 1(t-t^* = y)] + \zeta_o + \zeta_d + \zeta_t + X_{od,t}\phi + \varepsilon_{do,t} \quad (5)$$

where $\overline{ln(\frac{1-atr_d}{1-atr_o})}$ is the average log differential of the net of tax rates in the post-reform years. Then, $1(t - t^* = y)$ are indicator variables relating to the time since the reform happened in $t^* = 2011$. As such, π_y show the evolution of the stock ratios prior to the reform and the γ_y show the evolution following the reform. Multiplying by $\overline{ln(\frac{1-atr_d}{1-atr_o})}$ captures the intensity of the treatment and allows us to jointly estimate the effect of relative increases and decreases in one specification. The right panel of figure 5 shows no clear pre-trends – if anything, a slight downward trend – but an immediate level increase in the stock ratio following the reform; given the large jump on impact this may suggest tax evasion rather than real moves. The regions that lowered rates allowing residents to keep more, saw an immediate increase in the stock of top income taxpayers. To reduce noise in the post-reform period, the generalized event study design can also be presented as a simple dif-in-dif controlling for trends; the results are given in appendix A.6. The event study is reassuring because population changes do not pre-date the tax reform.

Finally, we conduct an exercise in the spirit of a placebo test using the pre-reform period. To do this, we take our measured tax differentials from 2011-2014 and lag them into the pre-reform period. We then match these post-reform tax rates to the years prior to the reform. We show in figure 6 that no significant correlation between the pre-reform stock ratio changes of the top 1% and post-reform tax rate changes exists. Nonetheless, the aggregate analysis cannot rule out confounding unobservables and potential taxable income responses. For this reason, we subsequently exploit individual data to control for all time varying regional characteristics and have proxies for counterfactual incomes.

4 Individual Analysis: Where to Move?

4.1 Methods and Identification

Although the aggregate analysis is appealing in its simplicity, we cannot rule out the possibility of unobservable time-varying region-specific covariates that are correlated with taxes and populations, i.e. although the tax rates may have come about from a random political process, the tax rates may not be random. To address this concern, we now use data for an individual tax-payer i who moves in year t. An individual enters the sample if the individual is in the top 1% in year t and relocates *across* regions between

t and $t-1$ (and only is in the sample in the year of move). Moves within a region are not included in our sample; we do not include these moves because some regions are composed of a small number of (or a single) provinces and we cannot observe moves if they are within the same province unless a municipality code is available. We only observe municipality codes for individuals living in sufficiently large cities and therefore do not use this information.[29] Subsequently, we will refer to an individual that moves regions as a "mover". We denote the alternative residential options (different regions within Spain) as j in our model. In particular, we focus on working-age movers in our estimating sample from 2006 to 2014; the vast majority of individuals move only once over the course of our sample but some individuals move multiple times in which case they appear in our data multiple times. For most individuals there will only be one time observation (but still J region observations). A "move" is a time-specific move which is indexed by (i, t) and the choice set for each move is indexed by j. One justification for focusing on movers is that local tax rates are likely a function of all individuals' location decisions. Because movers are a relatively small share of the population of a given region, it is likely that the equilibrium tax rates selected following the fiscal decentralization are driven by the large share of the stayers – reducing endogeneity concerns (Schmidheiny 2006; Brülhart *et al.* 2015). In addition, as noted in Schmidheiny (2006), "Households do not daily decide upon their place of residence. There are specific moments in any individual's life [first job, family changes, career opportunities] when the decision about where to live becomes urgent.... Limiting the analysis to moving households therefore eliminates the bias when including households that stay in a per se sub-optimal location because of high monetary and psychological costs of moving. However, the limitation to moving households introduces a potential selection bias when the unobserved individual factors that trigger the decision to move are correlated with the unobserved individual taste for certain locations."

Focusing on movers leaves us with a sample of 893 moves in the top 1%, of which

[29]Thus, our analysis uses a particular type of mover: those that move regions. Although data limitations are an important reason to focus on this type of move, this sample selection would be justified if tax differentials are important for individuals changing the labor market or region rather than changing houses within the same region.

approximately 330 are in the post-reform period, resulting in 13,395 move-region observations in our dataset. Focusing on movers may raise selection concerns, which could be addressed if we followed the approach of Moretti and Wilson (2017) to model the moving decision and the decision of where to move in a unified framework. The aggregate analysis discusses reasons why we elect not to follow this approach. Note that the aggregate stock analysis allowed "stayers" and "moving" residents to respond to taxes; in this section we study the effect of taxes conditional on moving regions. In appendix A.7, we also present results for the full sample of movers and stayers; the appendix also tests for differences in the characteristics of movers and stayers and finds no significant difference in average incomes prior to the move.

The dependent variable $d_{i,t,j}$ is coded one for the chosen region of residence for a given move (i,t) and zero for all other region that are not selected. In its most complex form, we estimate the following linear probability model where the *person-specific* tax rates from our tax calculator are denoted by $\tau_{i,t,j}$:

$$d_{i,t,j} = \beta ln(1 - \tau_{i,t,j}) + \alpha_{i,t} + \iota_{t,j} + \zeta_j \mathbf{x}_{i,t} + \gamma \mathbf{z}_{i,t,j} + \varepsilon_{i,t,j}. \tag{6}$$

Because we use moves pre- and post-reform, and because all taxes for a given individual are the same in the pre-reform period, the pre-reform period helps us to pin down other explanatory variables.[30] Our model contains individual move dummies denoted $\alpha_{i,t}$, alternative region by year dummies $\iota_{t,j}$, individual characteristics interacted with region dummies $\zeta_j \mathbf{x}_{i,t}$, and move specific covariates that vary across the choice regions $\mathbf{z}_{i,t,j}$. We will discuss each of these components in turn.

Following Bertoni *et al.* (2015), we estimate our model using a linear model rather than a McFadden-type conditional logit model. Given we have elected to utilize a linear model, we wish to highlight two important properties. First, predicted choice probabilities over all regions will add up to 1 for an individual i moving in year t. Second, an increase in the tax rate in one region does theoretically increase the probability of choosing this

[30] In all that follows, the very small tax differentials in the pre-reform period are not utilized. Including these differentials in the regression result in almost identical results given that taxes across regions were (almost) the same in the pre-reform era.

region while it decreases the probability of choosing any other region. Along both of these points, the presence of a fixed effect $\alpha_{i,t}$ for each move is critical because it forces the predicted probabilities to sum to one and therefore an increase in one region will lower the probability of the alternative regions; intuitively, this fixed effect adjusts the predicted probability from all other covariates by capturing the average deviation from the average probability.[31] However, the predicted probability of a mover selecting any one region need not be bounded between zero and one; even with this, the predicted probabilities across the choice regions will sum to one. The inclusion of $\alpha_{i,t}$ also forces identification of our parameter of interest to come from variation in tax rates across regions for a given move. In this way, we exploit the income tax differential across regions for a given tax payer which relocated. In the subsequent paragraphs, we discuss each of the components of this regression.[32]

Taxes. The theoretically appropriate tax rate, the "true-ATR", would be the actual effective average tax rate facing a given individual in a given region, which is a function of the individual's (possibly counterfactual) income in that region and the tax system in that region. Because this counterfactual is not observable to us, we use a "simulated-ATR" measure, which is the average tax rate for a given income level in a given region; this simulated tax rate is a function of the (assumed to be constant) income

[31]For ease of notation, we prove this for an equation with a single covariate denoted by $x_{i,t,j}$, the sum of the predicted probabilities for a given move (i,t) from our regression is given by

$$\sum_j (\widehat{\beta} x_{i,t,j} + \widehat{\alpha_{i,t}}) \quad = \quad \sum_j \widehat{\beta} x_{i,t,j} + \sum_j \widehat{\alpha_{i,t}} \quad = \quad \widehat{\beta} \cdot J \cdot \overline{x_{i,t}} + J \cdot \widehat{\alpha_{i,t}} \quad = \quad J \cdot [\widehat{\beta} \overline{x_{i,t}} + \widehat{\alpha_{i,t}}] \qquad (7)$$

where the upper-bar denotes an average over the j's. Given we have J alternative regions and, for a given move, only one region can be chosen:

$$\overline{d}_{i,t} = \frac{1}{J}. \qquad (8)$$

As shown in Greene (2003), the linear model implies that the estimated fixed effects, $\widehat{\alpha_{i,t}}$, are given by

$$\widehat{\alpha_{i,t}} = \overline{d}_{i,t} - \widehat{\beta} \overline{x}_{i,t} \Rightarrow \overline{d}_{i,t} = \widehat{\beta} \overline{x}_{i,t} + \widehat{\alpha_{i,t}}. \qquad (9)$$

Plugging (9) into (7) and using (8), proves that $\sum_j (\widehat{\beta} x_{i,t,j} + \widehat{\alpha}_i) = J \cdot \overline{d}_{i,t} = J \cdot \frac{1}{J} = 1$. This, then, necessarily implies that an increase in the probability of selecting one region must lower the probability of the alternative regions.

[32]Our estimation strategy of using a linear model comes with one caveat: unlike the standard multinomial choice model, our model assumes that the percentage point effects are constant. In other words, very small regions with very low baseline probabilities, would experience the same effect in percentage points as large regions with high baseline probabilities. However, given the inclusion of region by year fixed effects, we are controlling for characteristics like jurisdiction size that influence the baseline probabilities.

level across regions and the tax schedule in that region. In the baseline specification, the simulated net of tax rate is *person-specific* (not for a representative taxpayer). Specifically, because counterfactual wages are not observed to us, we use our tax calculator to construct the individual's average tax rate by assuming her income is constant across the regions. However, in practice and as shown by our theory which allows for wage capitalization to arise in spatial equilibrium (recall (2)), income may differ across the regions. In particular, a given individual is more likely to move to a high-income region all else equal. Given that taxes are progressive, by assuming that income is constant we will overestimate counterfactual wages (because we observe them in the selected, likely higher wage, region) and therefore overestimate counterfactual tax rates. This raises measurement error concerns, because the average simulated tax rates depend on the assumed to be constant income across regions and not the true counterfactual wages that may differ across regions. However, as noted in Kleven *et al.* (2013), the (individual's) marginal tax rate, the tax rate facing a given individual in a given region, proxies for the exogenous component of the ATR because it is independent of earnings and allows us to implement an IV strategy discussed below.[33] This also has the advantage of reducing measurement error in the average tax rate that might result from elements of the tax code not captured by our tax calculator. The variation in the marginal tax rate, across regions for the top 1% relative to other income groups is verified by looking at the within mover variation in appendix A.7. The variation across different regions a taxpayer could choose increases substantially from 2011 onward, and is much more pronounced for the top 1% of the income distribution.

Wage controls and sorting. Equilibrium wage differentials across regions may also be important to the choice of region. Although we assume wages are equal across re-

[33]Unlike Kleven *et al.* (2013) we cannot use the top marginal tax rate as an approximation for ATR because most individuals do not have income well into the tax bracket. Thus, we use the *mover's* marginal tax rate in the region as an instrument. In particular, consider and individual in the second highest tax bracket. For this individual we use the marginal tax rate in that bracket; we do not use the top tax rate on income. This allows us to identify our effect using individual variation in tax rates while also accounting for state by year effects. If changes in income across regions is small, the marginal rate is independent of earnings because it will not change the bracket the individual falls into. However, if changes in income across regions is large (for that person), then this may potentially result in the individual changing tax brackets. We address this issue subsequently in the paper.

gions to calculate taxes, wages may differ across regions and influence migration decisions irrespective of taxes. To control for unobservable counterfactual wages, we include location specific dummies interacted with characteristics of the mover (for example, age, age squared, male, and education). Denote the vector of characteristics interacted with region specific dummies as $\zeta_j \mathbf{x}_{i,t}$. This allows the returns to education and the skill premium to vary by region; by allowing observables to vary by region, these observable characteristics are used to account for unobservable counterfactual wages. Although motivated by wage differentials, this is a very rich parameterization that also can be interpreted as capturing any sorting of specific types of individuals to particular regions. For example, if high-educated or older individuals have a preference for locating in a particular region, this specification will capture this sorting.

Public services and regional shocks. Public services across regions matter. The inclusion of region by year dummies ($\iota_{j,t}$) captures any time varying policies – such as changes in public services – that are constant across all individuals in the top 1%. In general, however, we note that tax increases on the rich are not likely to change public services for the rich as these taxpayers are net payers into the tax system. Thus, in addition to accounting for regional policies, $\iota_{j,t}$ also account for time-varying amenities or economic shocks in the alternative regions that affect individuals in the top 1%. Unlike in the aggregate analysis, inclusion of these dummies is possible because we exploit mover-specific income to calculate tax rates rather than income for a representative taxpayer.

Other controls. Finally, moving costs between regions, which could be thought of as higher γ in our theory, also matter. To capture these moving costs, we include in a vector $\mathbf{z}_{i,t,j}$ a dummy variable that equals one if the region is the place of birth for the individual. We also include a dummy variable for the region of the principle workplace of the individual and a dummy variable that equals one if the individual had their first job in that region. Following a standard gravity model of migration (Bertoni *et al.* 2015), we also include the log of distance between the region of prior residence and each of the alternative regions. This captures the fact that nearby regions have lower moving costs because they allow individuals to maintain their social and family network.

Acknowledging the region of residence prior to moving plays a special role as it cannot be selected by a mover, we also include a dummy variable that equals one if the individual previously lived in the region. Note that these covariates can enter the regression even though they are time-invariant because they vary over the alternative j regions for a given individual i in year t.[34]

One important issues is the treatment of standard errors in this model. In particular, the dummy variables in (6) are related over the different regions j as only one option can be chosen for a given move. Further, tax policy is set by the region. First, we cluster over moves to resolve the first issue. Second, we cluster over destination region by year clusters to account for tax law in a region influencing all movers. In particular, it allows for correlation in errors across all movers for a particular region-year that may result, perhaps, from the common elements of the tax code that affect all individuals. We show the results for other treatments of standard errors (see appendix A.7).

Two additional selection issues arise. In terms of identification, selection concerns may arise because the sample excludes two Spanish regions because they operate autonomous fiscal systems; we treat these two regions as being "international" so that any concerns about moves to these regions are similar to concerns about moves abroad (these two regions also have their own languages, so moving to these regions may involve similar costs of moving abroad). This issue is common to prior studies of domestic migration that do not observe migration abroad. An additional concern arises because individuals appear in our estimating sample only when they move and thus the time dimension is unbalanced. If someone exits the top 1% and then moves, they would not appear in our sample. This type of exit from the sample would only be a concern if the individual exits the top 1% for reasons due to the income tax. In particular, this would result in us overestimating [underestimating] our effects if an individual that reduced their taxable income (enough to drop out of our sample) was also an individual that then elected to stay or move to a high-tax [low-tax] region. However, as discussed in the aggregate analysis,

[34]For example, for a mover, the place of birth dummy is one in the region of birth and zero in all other regions and thus varies within $\alpha_{i,t}$. Similarly, the place of origin dummy is one for the region of prior residence and zero for all alternatives, again, allowing it to vary across the j alternatives within $\alpha_{i,t}$.

appendix A.6 shows the taxable income response following the reform was small.

4.2 Baseline Results

Table 2 shows estimation of (6) using the average tax rate for each individual. Column (1) shows the results including $\alpha_{i,t}$ fixed effects and region by year fixed effects. The coefficient, 0.588, is the expected sign: a higher net of tax rate implies a higher probability of migrating to that region because the individual can keep more of what is earned. In terms of the magnitude, this coefficient implies that a one percent increase in the net of tax rate raises the probability of choosing a given destination by 0.59 percentage points. This represents a substantial increase in the probability of moving to a region, which if random would be 1/15. Subsequent columns of the table add various controls discussed above. This helps with the precision of our estimates, but the coefficient on the net of tax rate are stable – if anything, slightly increasing after accounting for these controls. Given that these variables richly control for counterfactual wage differences across regions and any possible sorting, this is very reassuring. Critical to our analysis is that column (2) containing no wage controls and column (7) containing a complete set of wage controls $(\mathbf{x}_{i,t} \times \iota_j)$ are not statistically different. The covariate adjusted coefficient is 0.90.

We have focused on the sample of movers across state lines where the role of taxes is particularly salient. To address selection concerns, we estimate a model using both stayers and movers in the top 1% and find a much smaller coefficient of 0.08. This is consistent with Akcigit *et al.* (2016) who estimate elasticities of domestic scientists around 0.03, but near 1 for foreigners.[35]

4.3 IV Approach

Kleven *et al.* (2013) adopt a grouping estimator a to construct the average tax rate by year $\times$ country $\times$ foreign status $\times$ quality. In their specification, quality serves a similar role as the, assumed to be constant, income level in our tax simulator. But, in our setting, by assuming that income is constant we may overestimate counterfactual wages (because we use income from the selected, likely higher wage region) and therefore overestimate counterfactual tax rates. This raises measurement error concerns because the simulated-ATR is a noisy measure of true-ATR in the non-chosen regions. In this section, to resolve

[35] Appendix A.8 uses a nonlinear model to show that our results are robust to the nonlinear model.

this issue, we instrument for the average tax rate with the mover-specific marginal tax rate, which is independent of earnings conditional on being in the same tax bracket. The relationship between the average and marginal rates is $ln(1 - atr_{i,t,j}) = \gamma + \delta ln(1 - mtr_{i,t,j}) + X_{i,t,j}\varrho + \varepsilon_{i,t,j}$. Given most individuals in the top 1% only have a fraction of income taxed at their marginal tax rate, δ is not as close to one as in Kleven *et al.* (2013) and for this reason, the marginal rate cannot simply be used as a proxy for the true-ATR.

Table 3 shows results using this IV strategy (appendix A.7 shows the reduced form with the marginal tax rate). As expected, the IV reduces attenuation bias concerns; the results are larger in magnitude. The first stage coefficient is the expected sign (positive), and is less than one given that a one point increase in the marginal rate raises the average rate by less than one point. The instrument is strong given changes in marginal rates at the top of the distribution are generally correlated with the pattern of changes lower in the income distribution. After instrumenting, a one percent increase in the net of tax rate increases the probability of moving to a region by 1.452 percentage points in our baseline specification and 1.731 percentage points in our most comprehensive estimating equation.[36] The intuition is clear: absent an instrument our tax sensitivity is estimated off of simulated net-of-tax differentials that are noisy measures of the counterfactual tax rate because we assumed that income is constant across regions, which due to attenuation bias results in underestimating the true coefficient of interest. Our instrument resolves this issue. These estimates suggest that – for example – the 0.75 percentage point differential in the average tax rate at mean income between Madrid and Cataluña in 2013 increases the probability of moving to Madrid by 2.25 percentage points. The effect of Madrid's 2014 tax cut of 0.38 percentage points further increases the probability of moving to Madrid by another 1.14 percentage points. Effects are larger at higher income levels in the top 1% because, for example, the average tax rate differential at 300,000 Euros is over two percentage points.

[36]We control in our estimation for the existence of wealth taxes in different regions across time by region-year dummies. As our data does not include the level of wealth, we cannot control for differential effects of different levels of the wealth distribution across regions. As a proof that our results are not confounded by this, we re-estimated the model for years prior to and including 2012 – when the wealth tax was initiated temporarily. This estimate is comparable.

We also estimate our model using the top 2% and top 3% of taxpayers. The effects fall off substantially and become insignificant after the top 1% of the income distribution. This may be due to the variation in tax rates in figure 2, which shows the divergence of tax rates is strongest – and most likely to overcome migration costs – for the top 1%. The divergence of tax rates across regions is not large outside of the top 1% and thus these "lower" income individuals are not much influenced by the reform unless they expect to see large income increases in the future. To formally test if the semi-elasticity varied across the income distribution (Lehmann *et al.* 2014), we would need equally salient tax changes for lower income groups exceeding their moving costs.

With respect to our instrument, the marginal tax rate may not be independent of earnings if individuals change brackets. Thus, the best instrument would account for the individual being in the same tax bracket for all regions. To analyze the importance of this, we remove any individuals from the analysis that are within χ% above or below all tax bracket thresholds for all regions. We show results for $\chi = \{1, 2.5, 5\}$. Thus, for $\chi = 1$, we remove anyone who is 3,000 Euro above or below the top tax bracket of 300,000 Euro, 1,750 Euro above or below the 175,000 Euro threshold, etc. Appendix A.7 shows that for $\chi = 1$ or $\chi = 2.5$, the results remain similar: a one percent change in the net of tax rate changes the probability of moving to a given region by approximately 1.8 percentage points. For $\chi = 5$, the results increase because the large cutoff removes a substantial fraction of "lower" income individual in the top percentile.

Given the IV only resolves measurement error concerns relating to counterfactual wages, one concern may be that the variation in tax rates across regions is not random. We conduct an exercise in the spirit of a placebo test to verify that post-reform tax rates are not correlated with unobservable characteristics that predict migration. We use the post-reform data to construct a placebo measure of tax rates in the pre-period. To do this, for each individual i and region alternative j in the Social Security data, we construct the mean tax rate in the post reform data (2011 to 2014). We use this tax rate as an explanatory variable to explain pre-reform moves to see if these post-reform tax rate differentials have any effect on the decisions pre-reform.

In table 4 column (1), we first show results using post-reform migration to show that taking the mean tax rate for each individual yields a very similar coefficient (2.05 versus 1.73 previously). In column (2), we restrict the sample to individuals that moved in the pre-reform period between 2005 and 2010 and implement the IV approach for these individuals using the placebo tax rates. The coefficient falls to 0.09. Post-reform tax rates are not correlated with unobservable factors that may have influenced pre-reform migration. This suggests to us the post-reform tax rates were not set in a way that was correlated with the observable migration patterns in the pre-reform period.

4.4 Heterogeneity

Although we have identified significant location choice effects, we have yet to determine if the location choices reflect real moves or simply tax evasion by misreporting the primary residence (perhaps to a second home). In order to shed light on this, we explore whether the tax changes have heterogeneous effects across different types of people within the top one percent by interacting the tax rates with indicator variables for various groups. Table 5 presents the results using the average tax rates.

In general, we do not find statistically significant differences across groups. This could be a result of characteristics not affecting the probability of where to move, but rather the ability to move per se. However, characteristics may also matter for where to move. One category that does have economically meaningful differences in the point estimates relates to education status; individuals with a higher education have a stronger influence of taxes on their location choices. This is consistent with these higher educated individuals having less job constraints and thus having a larger feasible set of regions to choose from. High educated households might also be more likely to seek the advice of a investment or tax consultant that might give advice on low-tax residential location. Unexpectedly, we also find larger effects for women.

In appendix A.7 we show results by job characteristics. In particular, we wish to see if the individual moves are driven by employment shocks or changes in the locations of jobs.[37] We focus on individuals that had a "non-voluntary stop" of their main contract

[37] In this section, we focus residential location choices by characteristics of the individual's job and firm. Alternatively, we could study the location of firms (*provincias del domicilio de la cuenta de cotización*

in the previous year or in the year of the move, individuals where the headquarter of the firm of their main contract moved, and individuals that changed their contract. In general we find very similar point estimates across all of the categories, however, one category is usually insignificant in each case. Given that the estimates are not statistically different from each other, we conclude that the increases in the probability of moving to a region are not being driven by firm-side responses.

4.5 Occupation and Industry

With the exception of Young *et al.* (2016), who focus on millionaires, the prior literature has been unable to answer the question whether policymakers can take the estimates derived for star scientists and athletes and apply these elasticities to the top of the income distribution more generally. The Spanish data we have access to is unique in that occupation and industry are reported in the data; this is not information that would be easily available when using U.S. tax return data. We test the generalizability of focusing on star scientists and athletes using these data. Although the number of athletes and star scientists are too small to focus on these groups specifically (see tables A.18 and A.17), we can aggregate to broader occupation/industry categories that allow us to study the heterogeneity across occupation and industry. This section also helps to inform the recent policy debate on the efficiency of tax schemes for top earners in specific occupations. Several OECD countries have preferential tax schemes for foreigners in high-income occupations. By focusing on the heterogeneity by occupation and industry, we can shed light on the efficiency of these tax schemes.

To determine if some industries or occupations are more responsive, we estimate (6) with an interaction of $ln(1 - \tau_{i,t,j})$ with dummy variables for occupation or industry categories. We show the results in figure 7 with precise point estimates in appendix A.9. When looking at the result for occupation, we identify the strongest effect for self-employed occupations; they are twice as large as all other occupations.[38] This is consistent

principal y/o segundaria) understanding that many high-income individuals have multiple contracts. Agrawal and Hoyt (2018), show that firms might relocate, however, in their model, this does not arise with purely residence-based taxation. Our focus is on individual migration in a residence-based system and not on firms.

[38]This result should be interpreted with the caveats discussed previously regarding income data reported for the self employed. The self employed are only included if they have a relationship with a firm

with these individuals being able to change their residence because their work location may also be flexible. Most of the other three broad categories have smaller degrees of responsiveness to each other. Although we have grouped the occupations based on skill, the occupation categories do not follow a natural hierarchy. Thus, we switch to industry classifications, where we use the one digit industry groupings in the data.

Figure 7 shows substantial heterogeneity by industry. We find the largest (and statistically significant) effects in the health, real estate, information, financial, and professional/scientific industries. Even within these groups, the effects in the health industry are three times larger than the financial industry. This heterogeneity may result, for example, from lower moving costs because of ease in relocating jobs. To compare this to the prior literature, athletes would fall under the category of arts and entertainment, while scientists could be under health or professional/scientific, which exhibit a very high degree of tax-induced mobility to lower tax regions. Our general takeaway from these results is that the responsiveness to taxes varies substantially depending on occupation and industry. Thus, these results provide a cautionary tale; the prior literature focusing on star scientists and athletes may not generalize to other occupations/industries.

5 Interpretation and Revenue Implications

An important policy question is how this reform affects tax revenue. For simplicity, consider a nonlinear tax schedule $T(y^i)$ where individual i earns income y^i, which is endogenous to the tax system because of taxable income responses. To proceed, assume that the top tax rate above the income bracket $\overline{y}$ is linear and given by $\overline{\tau}$. Define N, which is a function of taxes because of potential migration responses, as the stock of individuals above $\overline{y}$. To characterize the revenue maximizing top tax rate, follow the approach of Piketty and Saez (2013), maintaining all of their assumptions. Holding fixed taxes below $\overline{y}$ and perturbing $\overline{\tau}$ by $d\overline{\tau}$ and aggregating across individuals – letting y denote the average income in the top bracket – yields the total effect of top tax rate changes on revenue.

when generating the income. In other words, firms have to remit taxes for the services they contract. If, however, a self-employed has a relationship with a private individual, we cannot observe this income. We define self-employed as those which undertake business with firms. Given the level of income under consideration, we believe that a substantial share is included. Indeed, we verify in appendix A.9 that self-employed individuals have a majority of their income from non-labor income. Nonetheless, we may underestimate income (and therefore tax differentials) for these individuals.

The tax change will have three effects: a mechanical effect as a result of the change in the tax rate, an effect resulting from migration, and taxable income responses. Totally differentiating tax revenue, the change in tax revenue R can be decomposed into:

$$dR = \underbrace{[N(y-\bar{y})]\,d\overline{\tau}}_{\text{mechanical}} \underbrace{-\epsilon a\left[N(y-\bar{y})\frac{\overline{\tau}}{1-\overline{\tau}}\right]d\overline{\tau}}_{\text{taxable income}} \underbrace{-\eta N(y-\bar{y})\left[\frac{T(y)}{y-T(y)}\right]d\overline{\tau}}_{\text{mobility}} \tag{10}$$

where $\eta = \frac{dN}{N}\frac{(y-T(y))/y}{d[(y-T(y))]/y}$ is the stock elasticity (with respect to the average tax rate), $\epsilon = \frac{dy}{y}\frac{1-\overline{\tau}}{d(1-\overline{\tau})}$ is the elasticity of taxable income (ETI) and $a = \frac{y}{y-\bar{y}}$ is the Pareto parameter. Of course, this is a partial equilibrium analysis: it abstracts from spillovers from the presence of top earners to the income of, and thus revenues from, lower taxpayers; it ignores any other revenue effects obtained through other taxing instruments; and it assumes no fiscal externalities between the different governments and the federal government. One important limitation is that the elasticity of taxable income is calibrated rather than estimated. However, setting (10) to zero and solving for ϵ, we can obtain the critical value of the elasticity of taxable income necessary for a government to maximize revenue:

$$\widetilde{\epsilon} = \frac{1-\eta\left(\frac{T(y)}{y-T(y)}\right)}{a\left(\frac{\overline{\tau}}{1-\overline{\tau}}\right)}. \tag{11}$$

5.1 Revenue Effect in Euros

We estimate the revenue effects holding fixed the central government's tax rate at its 2014 level. We ask the question: at 2014 regional tax rates, how much does revenue change relative to if the region had simply mimicked the central government's tax rate on its tax base in 2014? Thus, for regions that raised their tax rate relative to the central government's tax rates, the mechanical effect is positive, but both the taxable income and mobility effect will be negative. For regions that decreased their tax rates relative to the central government tax rate, the effects will be opposite in sign.[39] The Pareto parameter

[39]This experiment is not designed to capture the effect of the changes in tax rates relative to 2010. Because the central government tax rate was also rising, this means all regional tax rates increased from 2010 to 2014. If this were the policy experiment, the taxable income response would be negative in all regions and the mechanical effect would be positive in all regions. When conducting the exercise this way, we similarly find the mechanical effect dominates. We want to calculate the revenue effects

is estimated using income data and the mobility elasticity using aggregate analysis. We estimate confidence bands using the parametric bootstrap. We assume the ETI is 0.15, which is slightly lower than the mid-point in the literature because the part of the tax base we analyze here excludes capital income. Appendix A.10 details the simulation assumptions.

Figure 8 shows the change in revenue resulting from the regional tax rates as a percent of total personal income tax revenue from all residents. The precise revenue effects with confidence bands are given in appendix A.10. The figure shows that in all circumstances, the mechanical effect of higher or lower tax rates is always the same sign as the total effect on tax revenue after accounting for all behavioral effects. This means that governments are on the left side of the Laffer curve: raising tax rates relative to the central government rate increases tax revenue in the regions. Madrid lowering its tax rate relative to the central tax rate corresponds to a decline in tax revenue from the top 1%. This lower tax rate results in revenue falling by 50 million Euro. However, taxable income only rises by 4 million Euro and the additional new high taxpayers contribute 9 million Euro more. Thus, the behavioral effect from migration is only 18% of the mechanical effect. The total change in revenue from the reform lowers tax revenue by approximately 0.42 percent of total personal income tax revenues in the region of Madrid. Although the stock elasticity is "large," if taxable income responses are small, progressive taxation remains a feasible means of raising revenue in the short-run. Of course, the calculation of the revenue effects has all the partial equilibrium caveats discussed above.

One limitation of this is that the elasticity of taxable income is calibrated rather than estimated. Thus, figure 9 shows the value of the ETI that is necessary for the region's deviation from the federal tax rate to result in the taxable income and mobility response exactly offsetting the mechanical effect. The figure indicates that this ETI must be between 1.02 and 1.34. These values are well outside the range of the best available estimates of this elasticity, which range from 0.12 to 0.40 (Saez *et al.* 2012), and suggest that our revenue conclusions are not driven by the calibration of this parameter.

holding everything else constant – including the federal tax rate. Further, we want to show the effect of decentralization, which is a deviation from the counterfactual federal rate and not changes over time.

6 Conclusion

We find that individual income tax changes result in a stock elasticity less than unity. In revenue terms, the behavioral effects induced by tax rate changes have a smaller effect on tax revenue than the mechanical effect resulting from a higher or lower tax rate. Although the migration response is significant, the taxable income responses are likely small meaning that the elasticity of the tax base is well below unit elastic.

Although the recent economics literature has seen an increase in research on migration, we are the first study to use population-representative administrative data in a country where taxes are purely residence based. Our revenue simulations suggest that changes in the stock of top taxpayers has minimal tax base effects. Thus, our results, at least in the short run, are consistent with Epple and Romer (1991) who show that local redistribution is feasible with migration, but in contradiction to Feldstein and Wrobel (1998) who show the opposite. Despite this finding, if the Spanish nation is viewed as the common labor market for high-income Spanish taxpayers, then coordination of redistributive policy could result in welfare improvements (Wildasin 1991). In the long run, mobility is likely to rise over time given demographic shifts and technological innovations, which may in turn impose added constraints on redistributive fiscal policy.

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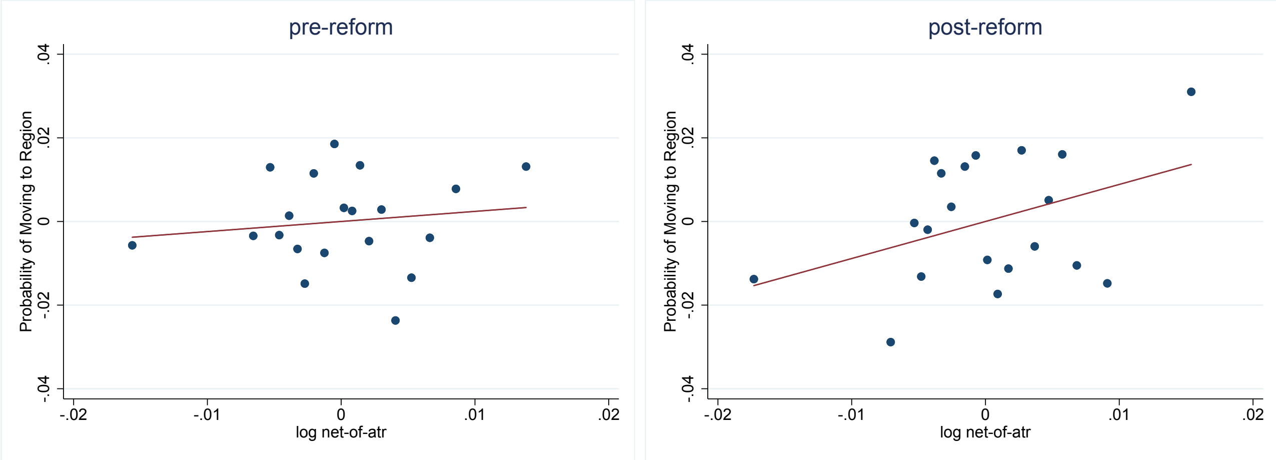
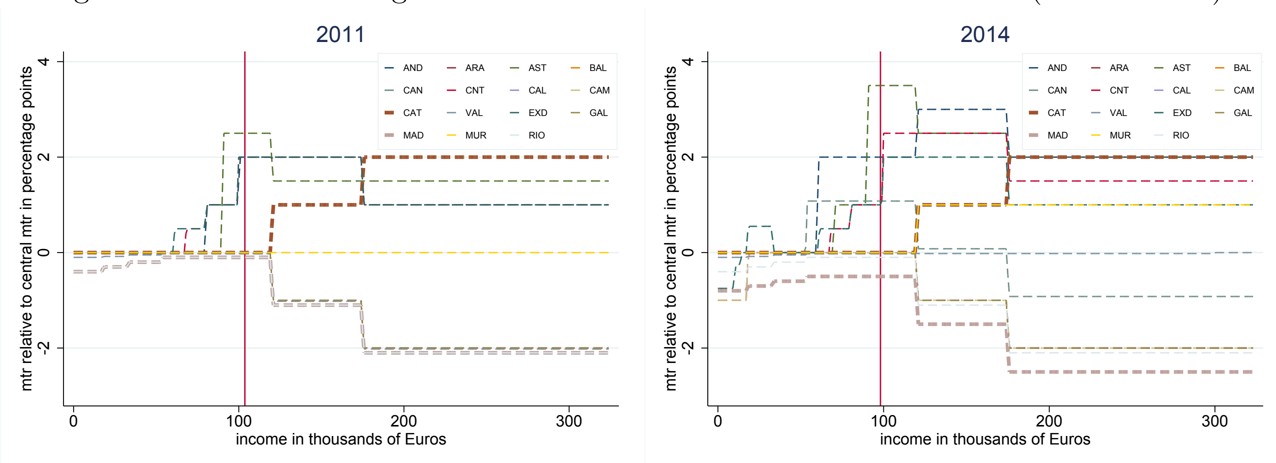
Figure 1: Location Choice and Taxes: Individual Data



The figure shows, using the sample of moves, the relationship between the probability of selecting a given region and the log of the net of tax rate. Each move appears fifteen times in the data, with one observation for each region. To construct the figure we regress a dummy variable for location choice (equals one if the mover selects that region and zero if the region is not selected) on a set of move dummies and region by year dummies. Then we regress the log of the net of tax rate on the same dummies. In the pre-reform period we use moves from 2005 to 2010 but use tax rates from 2011 to 2014 to see if post-reform tax rates have an effect on pre-reform migration. In the post-reform period we use moves from 2011 to 2014 and use the tax rates for those years. After each regression, residuals are binned into equally sized bins and a line of best fit placed through the binned data.

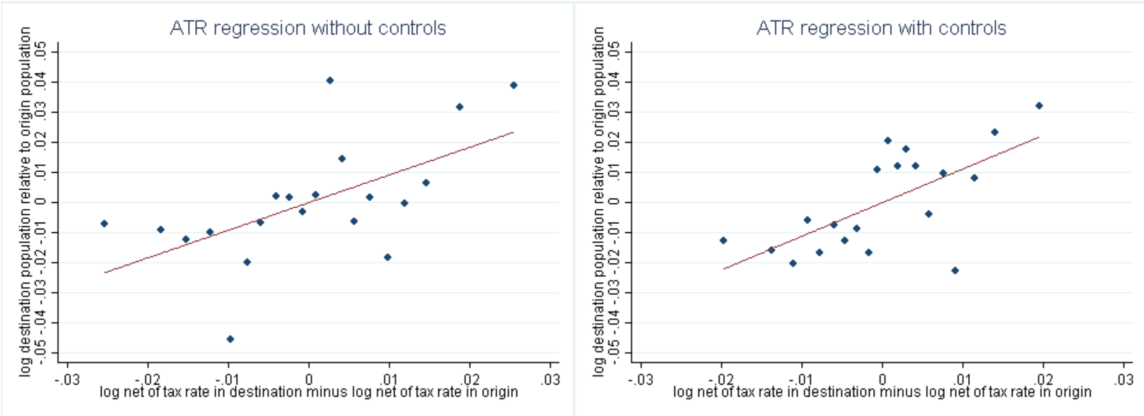
Figure 2: Tax Rate Changes Relative to Central Government Tax Rate (2011 & 2014)



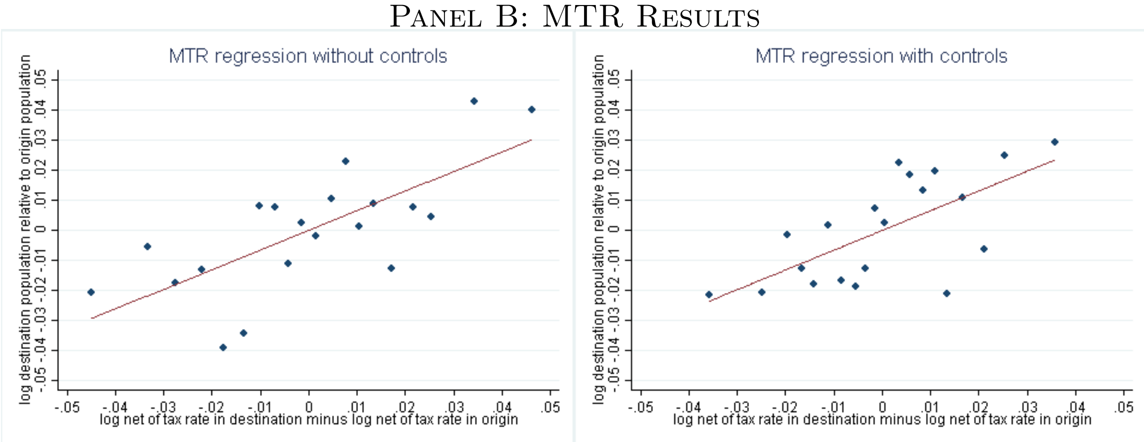
The graph shows the change in the marginal tax rates for each state relative to what the tax rate would be if the regions just copied the federal tax rate in that same year. This shows the deviations in 2011 immediately following the reform and in 2014 at the end of our sample. The vertical line shows the cutoff for the top 1%.

Figure 3: Effect of Taxes on the Stock Ratio

PANEL A: ATR RESULTS

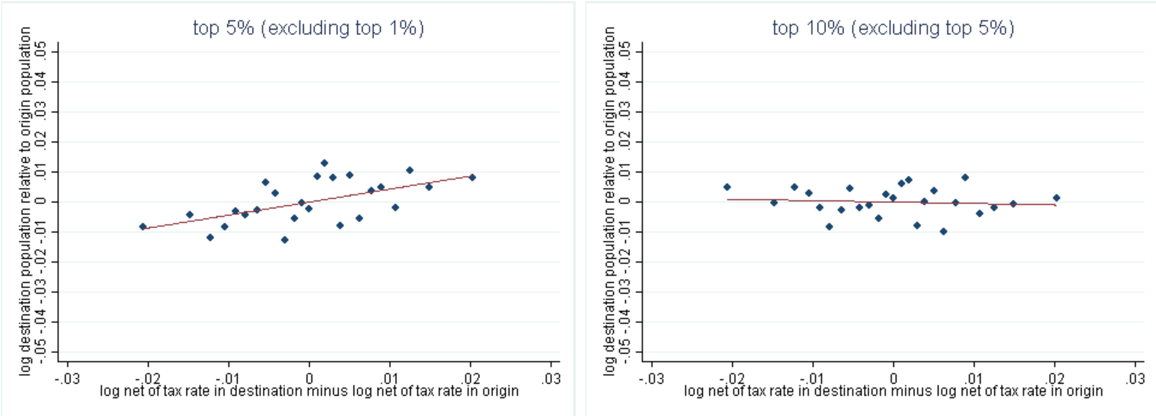


PANEL B: MTR RESULTS



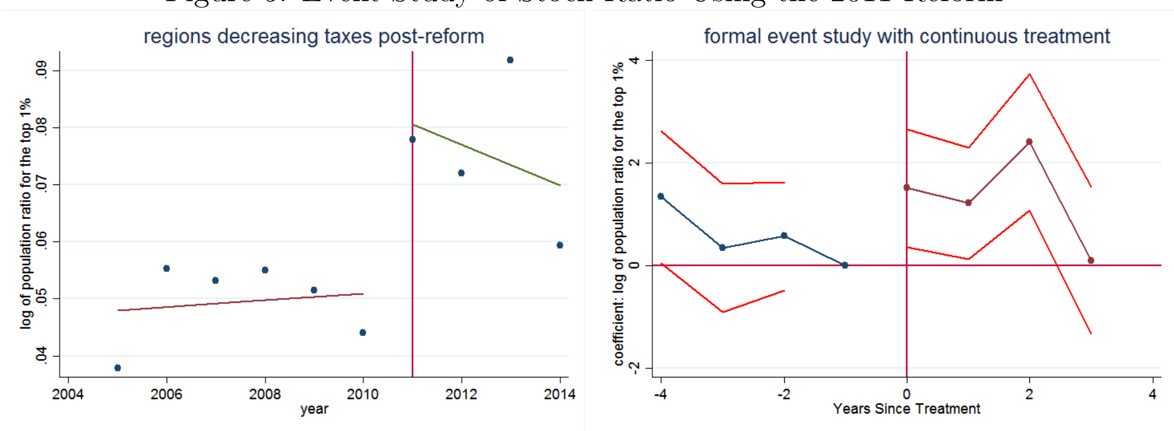
The upper panel shows a visual representation of the regression of the stock ratios on the average net-of-tax differentials, while the lower panel presents the regression of the stock ratios on the marginal-net-of tax differentials. The left panel excludes controls while the right panel includes controls in these regressions. To construct the figures, we regress the log of the stock ratio in region d (called "destination" for convenience) relative to region o (called "origin" for convenience) on the fixed effects, government spending controls, and controls to obtain the residuals. The tax variable is residualized in a similar manner. The figure plots the residuals in equal sized bins and shows the line of best fit. The provides both a non-parametric and linear estimate of the conditional expectation function. The theoretically expected effect is positive as keeping more money in the destination state means tax rates are lower, which implies more migration to the destination, increasing the stock.

Figure 4: Effect of Taxes on Stock Ratio: Heterogeneity Using Lower Income Groups



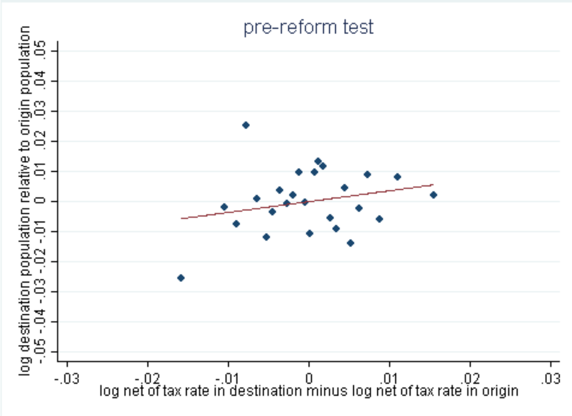
These figures are comparable to the upper right panel of figure 3 except they focus on lower percentiles of the income distribution. To construct the figures, we regress the log of the stock ratio in region d (called "destination" for convenience) relative to region o (called "origin" for convenience) on the fixed effects and controls and obtain the residuals. The tax variable is residualized in a similar manner. To remain comparable, we use the average tax variable for the top 1% to explain these lower-income stock ratios. The only difference from the prior figure is that we use the stock ratios of individuals outside the top one percent (the top 5% excluding the top 1% and the top 10% to 5%).

Figure 5: Event Study of Stock Ratio Using the 2011 Reform



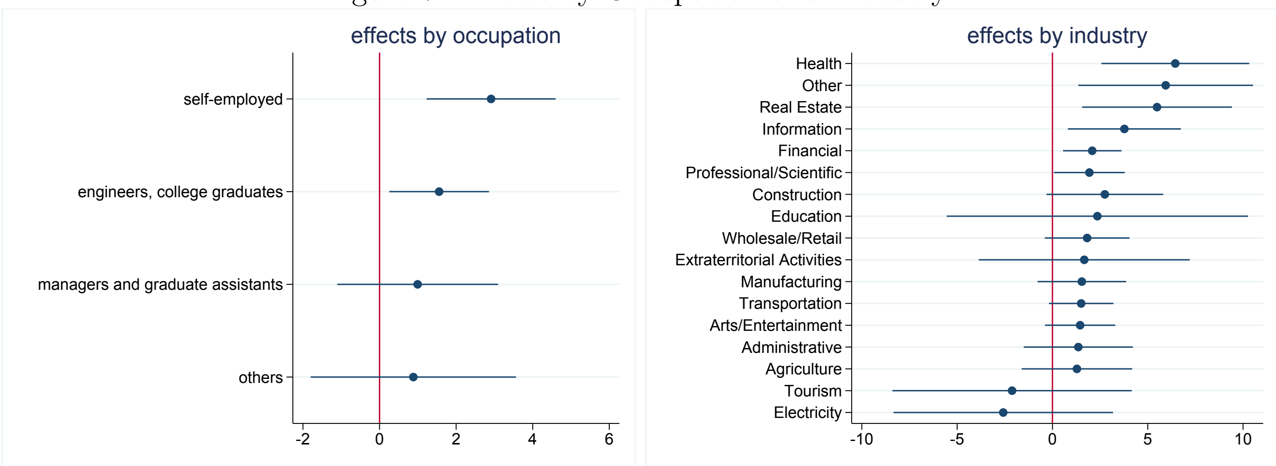
The left figure shows the raw averages of the stock ratios in region pairs where the net of tax rate increases in region d relative to region o following the reform. The stock ratio is the population in the top 1% of region d relative to region o. The right panel presents a formal event study where the treatment indicator is scaled by the average tax differential in the post-reform period between the region pairs. Thus, the vertical axis can be interpreted as the effect on the stock ratio of of a one percent increase in the net of tax rate in the destination region relative to the origin region.

Figure 6: Effect of Post-reform Taxes on Stock Ratio in the Pre-reform Period



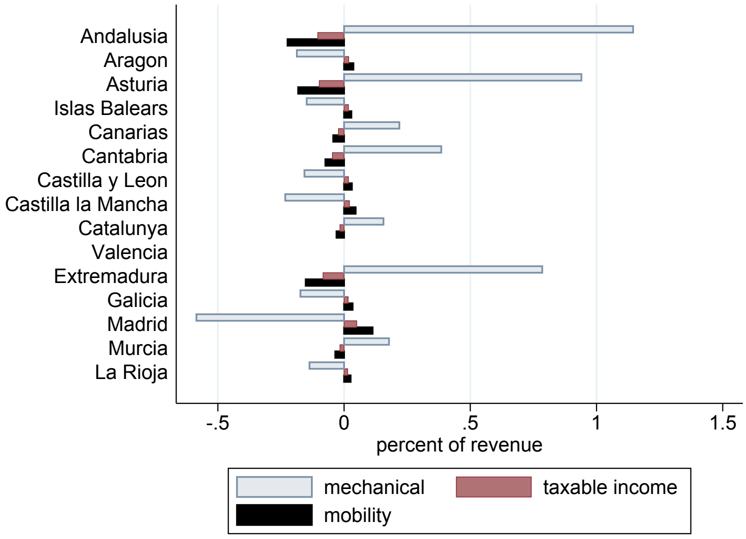
This figure only uses data on the stocks in the pre-reform period. We lag the tax variables into the pre-reform period to explain the regional stocks in the years prior to the reform. This figure is comparable to the upper right panel of figure 3 except for the use of only pre-reform moves and the time lag of tax rates. To construct the figure, we regress the log of the stock ratio in region d (called "destination" for convenience) relative to region o (called "origin" for convenience) on the fixed effects and controls and obtain the residuals. The (lagged) tax variable is residualized in a similar manner. The theoretically expected effect is zero given this is a placebo test. All figures use the same vertical/horizontal scale as the first figure in figure 3.

Figure 7: Effects by Occupation and Industry



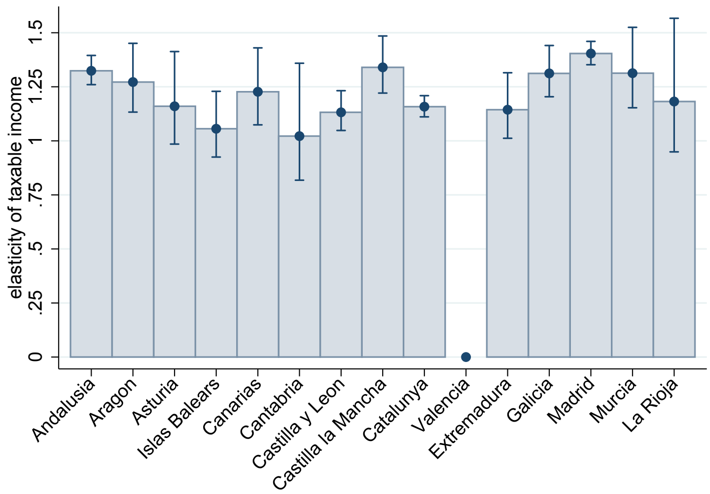
This figure shows the effects by occupation and industry with 90% confidence intervals around the point estimates. In the left figure, we show the effects by occupation (sorted by significance and then magnitude). Self-employed are those individuals that have a their longest contract with a registered firm. The "other" category includes all occupations not in the previous three groups; these occupations include non-graduate assistants, administrative officers, subordinates, administrative assistants, first and second class officers, third class officers and technicians, and labourers. In the right figure, we show the effects by industries.

Figure 8: Revenue Effects



The figure shows the breakdown of changes in revenue, as a percent of total personal income tax revenue raised. We consider the post-reform tax change relative to if the region had followed the central government tax rate. Thus, when the mechanical effect is negative this corresponds to the region lowering its tax rate; if it is positive, it corresponds to the region raising its tax rate. For this exercise we focus on tax changes on incomes above 90,000 Euros. We assume an ETI of 0.15. We estimate the Pareto parameter using our data and the mobility effect is taken from our estimate of the stock elasticity. The total effect is the sum of all three effects. We omit confidence bands for simplicity, but they are given in appendix A.10.

Figure 9: ETI that Would Result in No change in Tax Revenue from Regional Tax Changes



The bars show the critical elasticity of taxable income (given by (11)) on income above 90,000 Euros for which the regional deviations from the federal tax schedule would have resulted in the region observing no change in revenue. To obtain this elasticity, we estimate the Pareto parameter and use our estimated mobility elasticity from the aggregate analysis. We construct confidence intervals using the parametric bootstrap. Valencia simply mimicked the federal government and therefore is not included.

Table 1: Aggregate Analysis: Effect on Stock Ratios

	Average Tax Rate				Marginal Tax Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln[(1-atr_{d,t})/(1-atr_{o,t})]$	0.917*	1.116**	1.129**	0.878*	0.652**	0.656**	0.669**	0.556**
	(0.537)	(0.545)	(0.549)	(0.500)	(0.288)	(0.300)	(0.303)	(0.267)
Origin FE?	Y	Y	Y	Y	Y	Y	Y	Y
Destination FE?	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
Government Spending?	Y	Y	Y	Y	Y	Y	Y	Y
Demographic, Economic, & Amenity Controls?	N	Y	Y	Y	N	Y	Y	Y
Robustness Check			Control for Top Income Ratio	Adjust Stock Ratio for Churn in Income Distribution			Control for Top Income Ratio	Adjust Stock Ratio for Churn in Income Distribution
Number of Observations	1050	1050	1050	1050	1050	1050	1050	1050

The dependent variable is the log of the stock ratio, which is the number of individuals in the top 1% in region d relative to region o. The log of net of tax rate differential is the ratio of the net of tax rate in region d relative to region o and uses the average tax rate in the first four columns and marginal tax rate in the last four columns. The expected sign is positive. The last two columns in each set address potential taxable income responses by controlling for income in the top 1% and by adjusting the stock for the number of people that transition out of the top 1% relative to the prior year. The estimates represent the elasticity of the ratio. Standard errors allow for three-way clustering (state pair, origin-year, destination year). *** p<0.01, ** p<0.05, * p<0.1

Table 2: Individual Analysis: Average Tax Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1-atr_{i,t,j})$	0.588	0.714**	0.894***	0.712**	0.767**	0.714**	0.904***
	(0.420)	(0.343)	(0.336)	(0.337)	(0.336)	(0.343)	(0.332)
place of origin		-0.797***	-0.765***	-0.797***	-0.796***	-0.796***	-0.766***
		(0.061)	(0.060)	(0.061)	(0.061)	(0.061)	(0.060)
place of birth		0.207***	0.206***	0.207***	0.207***	0.207***	0.206***
		(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)
place of first work		0.185***	0.177***	0.186***	0.186***	0.185***	0.177***
		(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)
work place		0.288***	0.261***	0.288***	0.287***	0.287***	0.261***
		(0.018)	(0.021)	(0.018)	(0.018)	(0.018)	(0.021)
ln(distance)		-0.075***	-0.072***	-0.075***	-0.075***	-0.075***	-0.072***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
individual dummies	Y	Y	Y	Y	Y	Y	Y
j by year dummies	Y	Y	Y	Y	Y	Y	Y
j by education	N	N	Y	N	N	N	Y
j by age	N	N	N	Y	Y	N	Y
j by age squared	N	N	N	N	Y	N	Y
j by male	N	N	N	N	N	Y	Y
controls	N	Y	Y	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395	13,395	13,395	13,395
number of moves	893	893	893	893	893	893	893
R^2	0.122	0.278	0.302	0.279	0.280	0.279	0.304

In all specifications, the estimating sample uses pre- and post-reform moves in the top 1% of the income distribution. Each move has fifteen observations: one for each possible alternative region. The dependent variable equals one if the region is selected. This table uses the *person-specific* average tax rate as the independent variable. All standard errors are clustered two-ways: region-year clusters and move (i, t) clusters. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Individual Analysis: Average Tax Rates with IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1-atr_{i,t,j})$	1.452	1.542*	1.711**	1.510*	1.614**	1.534*	1.731**
	(0.948)	(0.788)	(0.791)	(0.789)	(0.792)	(0.787)	(0.797)
place of origin		-0.797***	-0.766***	-0.797***	-0.796***	-0.797***	-0.766***
		(0.061)	(0.060)	(0.061)	(0.061)	(0.061)	(0.060)
place of birth		0.207***	0.206***	0.207***	0.207***	0.207***	0.206***
		(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)
place of first work		0.185***	0.177***	0.186***	0.186***	0.185***	0.177***
		(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)
work place		0.288***	0.261***	0.288***	0.287***	0.287***	0.261***
		(0.018)	(0.021)	(0.018)	(0.018)	(0.018)	(0.021)
ln(distance)		-0.075***	-0.072***	-0.075***	-0.075***	-0.075***	-0.072***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
individual dummies	Y	Y	Y	Y	Y	Y	Y
j by year dummies	Y	Y	Y	Y	Y	Y	Y
j by education	N	N	Y	N	N	N	Y
j by age	N	N	N	Y	Y	N	Y
j by age squared	N	N	N	N	Y	N	Y
j by male	N	N	N	N	N	Y	Y
controls	N	Y	Y	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395	13,395	13,395	13,395
number of moves	893	893	893	893	893	893	893
R^2	0.122	0.278	0.302	0.279	0.280	0.278	0.304
First Stage Coefficient	0.392***	0.392***	0.392***	0.392***	0.391***	0.392***	0.391***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
F-statistic	735.1	740.2	745.6	740.2	795.6	740.9	792.9

In all specifications the estimating sample uses pre- and post-reform moves in the top 1% of the income distribution. Each move has fifteen observations: one for each possible alternative region. The dependent variable equals one if the region is selected. This table uses the *person specific* average tax rate and instruments for it with the person-specific than marginal tax rate. All standard errors are clustered two-ways: region-year clusters and move (i, t) clusters. The bottom panel shows the first stage relationship between marginal and average tax rates. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Placebo Test

	(1)	(2)	(3)	(4)
	Average Tax		Marginal Tax	
	Post-Reform	Pre-Reform	Post-Reform	Pre-Reform
$ln(1-atr_{i,t,j})$	2.051***	0.093	0.866***	0.038
	(0.687)	(0.469)	(0.281)	(0.194)
individual dummies	Y	Y	Y	Y
j by year dummies	Y	Y	Y	Y
$\zeta_j \mathbf{x}_{i,t}$	Y	Y	Y	Y
controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y	Y
observations	4,965	6,180	4,965	6,180
number of moves	331	412	331	412
F-statistic	797.9	509.1		

This table shows results of a placebo test by verifying that post-reform tax rates have no significant effect on pre-reform migration patterns. The post-reform sample is restricted to migrants in the post-reform period, while the pre-reform sample is restricted to individuals moving in the pre-reform period. To do this, we construct the mean tax rate for each alternative and individual in the post-reform period 2011-2014. Column (1) and (3) shows that even using this mean tax rate, we can reproduce our results. Columns (2) and (4) then use migration decisions in the period 2005-2010 but using the mean tax rates constructed from the period 2011-2014. Column (1) and (2) uses the person specific average tax rate and instruments for it using the marginal tax rate. Columns (3) and (4) uses the marginal tax rate. All standard errors are clustered two-ways: region-year clusters and move (i, t) clusters. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneity of Effects by Personal Characteristics

$ln(1 - atr_{i,t,j})$	(1)	(2)	(3)	(4)
Younger than 40	1.680*			
	(0.862)			
Older than 40	1.759**			
	(0.846)			
Kids		1.767*		
		(1.031)		
No Kids		1.709**		
		(0.769)		
Men			1.483*	
			(0.864)	
Women			3.012**	
			(1.221)	
University Degree				2.185***
				(0.842)
No University Degree				1.008
				(1.045)
individual dummies, j by year dummies, $\zeta_j \mathbf{x}_{i,t}$, and controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395
number of moves	893	893	893	893
F Statistic	295.7	226.1	367	581.9

The net-of-tax rate is interacted with an indicator variable for the group category. This table presents results for the average tax rate. We instrument for the net of average tax rate using the net of marginal tax rate for the individual. The interaction term is instrumented for using the instrument interacted with the indicator variable for the group. All standard errors are clustered two-ways: region-year clusters and individual move (i, t) clusters. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

A Appendices (Online Only)

A.1 Correlation of State Characteristics and Tax Changes

In this section, we show that the size of the state tax changes following the reform are not statistically associated with characteristics of the top 1% in the pre-reform period. In particular, the pre-reform in-migration rate, the stock of individuals in the top 1%, and the number of top 1% movers to not appear to predict the size of the tax change. Given that this analysis is limited to a cross-section of regions, this analysis is simply meant to be descriptive. Nonetheless, these types of variables also have small coefficients. The variables with large coefficients are the presence of a right wing government, debt per capita, and incomes in the region. Although not statistically significant, the large coefficients suggest these may be more important factors. This helps to allay concerns that governments changed their tax rates because they had expectations about how the migration rates of the top 1% or the stock of the top 1% in their region would respond. The results are shown in table A.1 where the dependent variable is the size of the tax change and in table A.2 where the dependent variable is a dummy that equals one if the region became high-tax.

A.2 Transition Matrix

Tables A.3 and A.4 show the transition matrix between regions for individuals in the top 1% of the income distribution. The first table shows the transition matrix for the post-reform era and the second table shows the transition matrix for the pre-reform era. These numbers represent the total number of migrants observed in our 4% random sample of the population. To obtain full population numbers multiply by 25.

A.3 Tax Calculator

This section introduces our tax calculator which computes marginal and average tax rates for all individuals in fifteen regions of Spain from 2005-2014. The Spanish income tax is a dual tax which applies progressive taxes on labor income (which can be changed by region) and taxes capital income separately (cannot be changed by regions). The capital tax base does not have an influence on the progressivity of the labor tax base. This tax calculator only computes the average and marginal tax rates for the labor tax base and takes into account the basic deductions and tax credits for ascendents and descendents as described below. Given this, the tax calculator is written to be accurate for top income taxpayers and should not be used to study low-income households where credits and deductions are much more important.

The tax calculator takes into account regional variation in marginal tax rates, tax bracket thresholds and the basic deductions given by the variables in the input data table. However, other specific deductions are ignored, as they fade out with income and do in general not affect substantially the higher part of the income distribution. Thus, to reiterate, our tax calculator should only be used for studying high-income taxpayers where the role of these deductions are small. Information about marginal tax rates, deductions and tax brackets are taken from the annual **Manual Práctico** published by the Spanish ministry of finance.[40]

Structure of input data

The tax calculator consists of a STATA *.do* file which runs over a data-set with the variables given in table A.5. These input variables allow us to construct an average and marginal tax rate for each person for all years and states in the data set. Tax rates and bracket thresholds are not inputs in the data set because they are coded directly into the *.do* file which feeds in income and characteristics for each individual.

Output data

The output are given by the variables in table A.6 for each person identifier (id) for all states and years in our data. As an example, we present in table A.7, tax rates for a hypothetical tax payer, born 1970 with an income of 300,000 Euro and one child and all other inputs set to zero.

A.4 Summary Stats

Table A.8 shows summary stats for the top 1% (and as a comparison for the next percentile). The summary statistics are for movers only. As is clear, only 1 out of 100 individuals in the top one percent migrate in the post-reform period. We present statistics for income following their move, such that the income statistics presented here are in the new place of residence. Income among movers was declining over this time period. It was also very noticeable that average income for the top 1% and 2% are very different; the dramatic fall in income after the top percentile justifies our focus on this elite group. We also present the tax rates for the group. Focusing on the marginal rates, all individuals in the top 1% were in the 45% federal government tax bracket prior to 2007. In the post-reform period, these tax rates increases on average and began to diverge.

A.5 Justification of Stock Model of Migration

Moretti and Wilson (2017) estimate a flow model of migration. Let o index the origin and d index the destination in year t. The reduced form is given by:

$$ln(P_{odt}/P_{oot}) = \beta[ln(1 - atr_{dt}) - ln(1 - atr_{ot})] + \zeta_o + \zeta_d + \zeta_t + \nu_{odt}. \qquad \text{(A.1)}$$

[40]The zip package of the tax calculator contains all documents for all years in the folder *tax law*.

The left hand side variable $ln(P_{odt}/P_{oot})$ is the log odds ratio where P_{odt} is the share of the population that moves from state o to state d in year t and P_{oot} is the fraction of the population that stays in state o in the same year. On the right hand side of the estimating equation are fixed effects given by ζ including: origin fixed effects, destination fixed effects, state pair (or origin by destination fixed effects) and time fixed effects. The net of tax rate with respect to the average rate is given by $1 - atr_{dt}$ $[1 - atr_{ot}]$ in the destination [origin].

Unlike Moretti and Wilson (2017), we prefer using a stock rather than flow model of migration in our aggregate analysis. In particular, notice that the log odds ratio will be missing whenever there is no migration between regions. Given we only have a 4% sample of the full population, this means we have a large number of missing observations for which migration may actually exist, which raises selection concerns. Second, our panel is much shorter than that of Moretti and Wilson (2017) which prevents us from being able to do important robustness checks as in their paper. Finally, we are missing two regions in Spain and thus "out-of-data" migration may be important.

In addition, the identification strategy in Moretti and Wilson (2017) fundamentally relies on a diff-in-diff approach, but where the outcome is migration flows across regions rather than stocks of top earners across regions. Compared to a standard random utility model where individuals decide every period where to locate, irrespective of where they are, these flow specifications rely on a model where utility of being in any location is always conditional on where individuals are located to start with in period t (the origin region). Identification relies on the assumption that moving costs are asymmetric across regions. This assumption has an important consequence: it generates some non-random permanent migration flows across regions that do not come from changes over time in amenities / characteristics across regions. In terms of identification, this means that the strategy is a little bit different from what is usually done in location choice models. Traditionally, the identification relies on the assumption that, absent tax changes, differences in stocks of individuals across regions are fixed over time. In the flow model, the assumption is that region-pair migration flows are fixed over time. For this reason, and given the large number of pairs with no observed migration flows and the length of our sample, we prefer the stock analysis.

A.6 Aggregate Analysis

Table A.9 shows the event study as a standard difference-in-difference, including a specification where we control for trends from the time of the treatment. We use a binary treatment that equals one if a region increased its net-of-tax rate relative to the other region pair. We verify an elasticity of taxable income that is less than 0.30 and is statistically insignificant in figure A.1.

A.7 Individual Analysis

Figure A.2 shows the within individual variation in tax rates across the regions. As is clear, this variation jumps up almost immediately following the reform and is a much larger increase for the top 1%, which justifies our focus on this group.

Table A.10 shows a test of means for the characteristics of movers versus stayers. The goal of this table is to see if our sample is different from the full population. For this reason, we use pre-migration income as it is the relevant income to verify if a selection problem existed. No difference in pre-reform income exists between movers and stayers, however, people do eventually move to higher wage regions, which justifies our IV strategy. Movers are different on some demographics: they are younger and higher educated.

Table A.11 estimates the model using the full sample of movers and stayers. The effect of taxes on the full sample including stayers is small and insignificant. This is consistent with the discussion in Schmidheiny (2006) where the inclusion of stayers results in using many individuals that are in a per se sub-optimal location because of migration frictions. The table also shows results in column (2) using within region movers and across-region movers and in column (3) using only within state movers. As is evident, the effects are smaller than those presented in the text and are marginally insignificant at the 10% level. This sample of moves, however, omits any within state moves for which we do not have precise local residence locations in the data. For this reason, columns (2) and (3) should be interpreted with caution.

Table A.12 shows various treatments of the standard errors. As is evident, the standard errors are similar.

Table A.13 is analogous to table 2 except instead of using the average tax rate, it uses the marginal tax rate (person-specific). Results are smaller in absolute value because the marginal tax rate increases the average tax rate by less than one-for-one.

Table A.14 shows a robustness check that removes individuals near the bracket thresholds of any state. The justification that the marginal tax rate is independent of counterfactual earnings requires individuals do not change tax brackets across the various alternative regions. This could happen if an individual is close to any tax bracket across all of the j alternatives. Thus, to verify the instrument is robust to this possibility, we exclude individuals that could possibly change brackets because they are near any state level threshold. The results are very similar to our baseline IV estimates.

Table A.15 shows the effects by job characteristics. Overall, our conclusion is that taxes have a significant effect on location choices and that this result is highly stable across various specifications, sample restrictions and robustness checks. Table (A.19) and (A.20) show the point estimates and standard errors for the figures presented in the text relating to occupation and industry.

A.8 Individual Analysis: Non-linear Models

As an alternative to the linear model we estimate, (6) could be estimated by a multinomial logit model. This, however, results in convergence problems for many specifications or necessary adjustment of the convergence threshold given the large number of binary regressors included. To convince the reader that our OLS model is valid, Table A.16 presents the final specification from 3 in the text, but estimates the coefficient by a conditional logit model. This implies a large flow elasticity consistent with our OLS approach.

A.9 Occupation and Industry

Tables A.17 and A.18 show the occupation and industry of the most common categories of migrants from the top 1% in the post-reform period. Most industries and occupations are high-skill and previously studied subgroups such as athletes feature prominently in the distribution. Nonetheless, access to nationally representative Social Security data allows us to study a much broader set of occupations and industries than many studies in the prior literature. It also paints a picture of what the top 1% of the income distribution looks like in Spain. As noted in the text, we can classify the main contract of an individual as self-employed, however, we only observe income if the individual has a contract with a reporting firm. To verify we are classifying the self-employed correctly, in figure A.3 we show all the sources of income for each income category. The key to this figure is that individuals we classify as self-employed have the majority of their income from the "economic activities" category, which includes self-employment income.

Table A.19 shows the results by occupation. We present two set of results. In the first column for each occupation category listed, we show the effect on the probability of moving to a region relative to all other occupation categories. In the second column, we show the results in a particular occupation relative to all other occupations listed in only the lower panels in the table. In column (5), we present results from a single estimating equation where taxes are interacted with each of the occupation category dummy variables.

In table A.20 we focus on the results by industry.[41] We present two sets of results.

[41] Detailed industry categories we use are (1) Agriculture, forestry, and fishing, (2) Manufacturing, (3) Electricity, gas, steam, and air conditioning supply, (4) Construction, (5) Wholesale and retail trade, repair of motor vehicles and motorcycles; accommodation and food service activities, (6) Transportation and storage, (7) Accommodation and food service activities (8) Information and communication, (9) Financial and insurance activities (10) Real estate activities, (11) Professional, scientific, and technical activities, (12) Administrative and support service activities, (13) Education, (14), Human health and

In the upper panel, using a model that interacts the taxes with a particular dummy variable for industry k, we present the results in a particular industry relative to all other industries in the data. The second row showing the effects in all industries other than k has the flavor of a leave-one-out procedure that allows us to test the sensitivity of the estimates if we remove one industry. The results indicate that the coefficients generally remain stable. This is reassuring because it informs us that our results are not driven by a single industry. However, the first row, which represents the effect in industry k shows substantial heterogeneity. This is confirmed in the second panel of table A.20 where we estimate a single estimating equation where taxes are interacted with dummy variables for each particular industry. We confirm substantial heterogeneity by industry the second panel of table A.20 where we estimate a single estimating equation where taxes are interacted with dummy variables for each particular industry.

A.10 Empirical Estimation of Revenue Response

To empirically estimate the revenue response we follow the following steps. This procedure accounts for the fact that the actual tax system contains many brackets above $\overline{y}$.

1. We pick a value of $\overline{y}$ that we wish to focus on. We consider 90,000 Euro which corresponds to the top 1% threshold.

2. We construct a dataset of individuals with incomes above this value of $\overline{y}$ and we calculate what their average tax rate would be in year t if they earned $\overline{y}$ using our tax calculator ($T(\overline{y})/\overline{y}$). Given we know what their average tax rate on their true income from our prior simulation of their tax rates, we use these two pieces of information to calculate what their marginal tax rate is on income above $\overline{y}$. In particular, solving $T(y) = T(\overline{y}) + \overline{\tau}(y - \overline{y})$, we calculate the marginal tax rate for each individual on income *above* the threshold as $\overline{\tau} = \frac{T(y)-T(\overline{y})}{y-\overline{y}}$ where y is true income, T is the taxes paid as a function of income. We then appropriately partition $\overline{\tau}$ to its regional and central component.

3. Using the dataset we also calculate the total stock of individuals with income above the threshold in each region (and in all of Spain).

4. We fit the Pareto distribution separately for each region on the individuals with income above $\overline{y}$ and calculate the Pareto parameter and its corresponding standard error.

social work activities, (15) Arts, entertainment, and recreation, (16) Activities of extraterritorial organizations and bodies, and (17) Other, which includes all other industry codes that have only a small number of observations including water supply, sewage, waste management and remediation activities; and public administration and defense; compulsory social security.

5. We then calculate the mean income and mean tax rates in each region of Spain, which is equivalent to collapsing our data at the region by year level.

6. We apply our theoretical model using:

   (a) $\overline{y}$ is approximately 90,000 Euro (the threshold for the top 1%)

   (b) y is the average income of individuals above $\overline{y}$ in each state. We calculate this as the average income in the post-reform years in each region to minimize the threat of year specific shocks to income. The results are robust to using pre-reform numbers.

   (c) $d\overline{\tau}$ is the regional tax rate minus the central government tax rate. To account for the fact that some small differences existed prior to the reform, we subtract off the regional tax rate net of the central government tax rate in 2010 for the few regions that had some differences prior to the reform.

   (d) $T(y)$ is the tax payment the individual would have faced on income of y.

   (e) N is the total stock of people above $\overline{y}$. We calculate this as the average number of individuals in the state with income above $\overline{y}$ in the post reform years. The results are robust to using pre-reform numbers.

   (f) a and its standard error are estimated by fitting the Pareto distribution to the top 1% in each region.

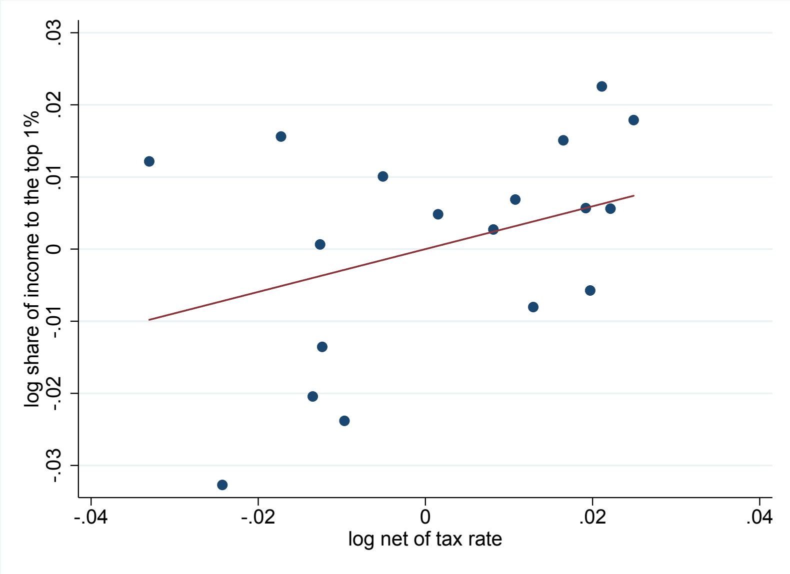
   (g) the stock elasticity η and its standard errors comes from our estimates of β.

   (h) ϵ is set as 0.15 in our baseline simulation, but we show the results are robust for a range of values.

7. Given these values, we can simply apply the formulas in the text and use the parametric bootstrap to construct confidence bands. Given we assume no fiscal externalities, we assume the federal tax rate is zero, which is appropriate under separate partitioning of the regional and federal income tax bases.

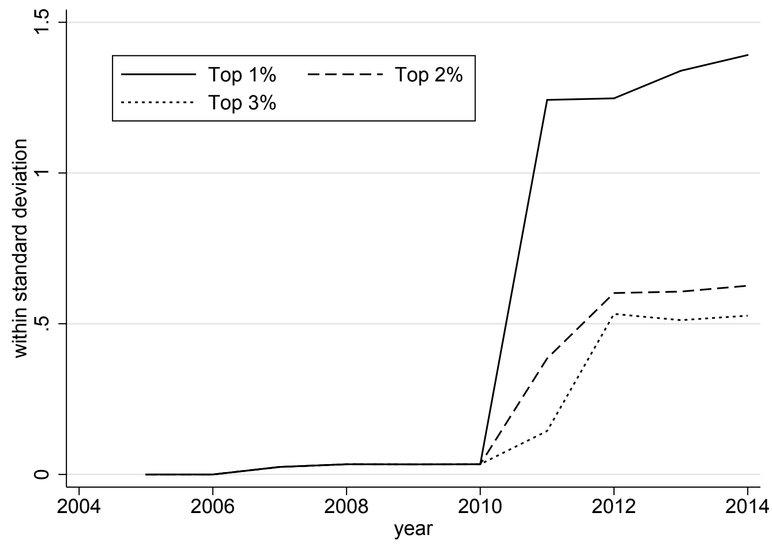
The numerical results and standard errors, resulting from the parametric bootstrap, are presented in table A.21

Figure A.1: Taxable Income Response



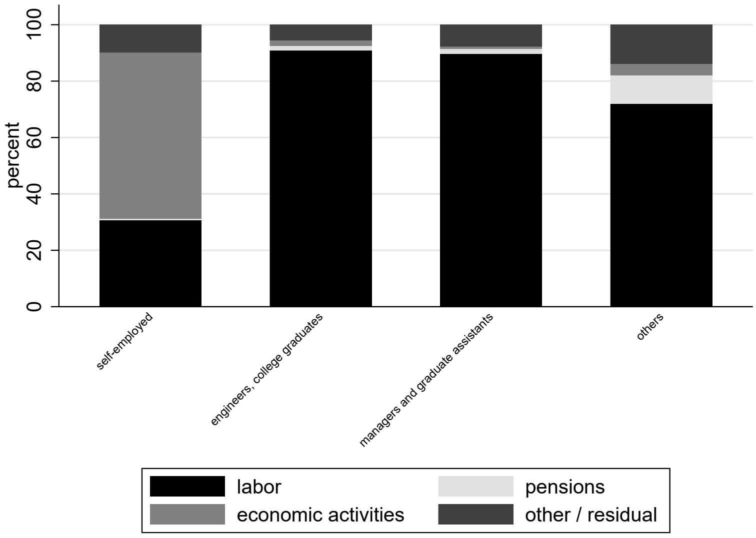
This figure shows results of a panel data regression of the form $ln(share_{r,t}) = \zeta_t + \zeta_r + \kappa ln(1 - mtr_{r,t}) + \nu_{r,t}$ where $share_{r,t}$ is the amount of income earned by the top 1% in region r in year t divided by the total income earned in the region. Thus, this variable is the share of income earned by the top 1%. When calculating income, we use income of the working age population. The explanatory variables include $1 - mtr_{r,t}$, the net of tax rate for the top tax bracket, region fixed effects and year fixed effects. We use data from 2005 to 2014. The parameter κ captures the elasticity of taxable income and is shown in the graph above. To construct the figure, we regress the log of the share on fixed effects. The same is done for the tax variable. We predict the residuals and bin the residuals to visualize the results. The ETI is insignificant.

Figure A.2: Tax Rate Variation Over Time



The graph shows the standard deviation within individual moves of marginal tax rates across alternative regions from 2005 to 2014 for different percentiles of the income distribution. Increasing variation indicates increasing dispersion of marginal tax rates across regions for a taxpayer.

Figure A.3: Income Breakdown by Occupation Classification



This figure shows the sources of income by occupation category: labor income, pension income, economic activity (self-employment) income, and other income. Our classification of self-employed individuals shows that they have the majority of their income from economic activities.

Table A.1: Correlation of Tax Changes and Pre-reform State Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
in-migration in the top 1%	-0.116									1.061
	(0.105)									(0.603)
in-migration in the top 3%		-0.177								-1.548
		(0.119)								(0.920)
in-migration in the top 10%			-0.165							0.769
			(0.120)							(0.666)
top 1% observations				0.067						4.999
				(0.388)						(3.342)
top 1% movers					-0.213					-5.365
					(0.450)					(3.499)
right wing government						-1.030				-1.289
						(0.809)				(0.937)
debt per capita							-3.005			1.171
							(7.524)			(9.243)
log of income in top 1%								-9.284*		-7.352
								(5.118)		(5.979)
log of income tax revenues									-0.303	0.377
									(1.678)	(1.513)
Constant	4.125***	4.430***	4.281***	2.844	3.912**	3.785***	3.637***	114.494*	4.338	75.693
	(0.899)	(0.900)	(0.858)	(2.321)	(1.493)	(0.591)	(1.093)	(61.328)	(6.128)	(72.238)
Observations	15	15	15	15	15	15	15	15	15	15
R-squared	0.087	0.144	0.127	0.002	0.017	0.111	0.012	0.202	0.002	0.763

This table shows the correlation between the size of the top marginal tax rate change at the state level between 2010 and 2011 and share of in-migration in the top 1% (column 1), 3% (column 2), and top 10% (column 3); the total number of observations (column 4) and movers (column 5); a dummy for right wing regional governments (PP, CC, and CiU; column 6); regional debt per capita (column 7), average income in the top percentile (column 8); and log income tax revenues (column 9). Column 10 uses all variables. All values are for the year prior to the reform: 2010. *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Correlation of High-Tax Dummy and Pre-reform State Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
in-migration in the top 1%	-0.036									0.338
	(0.033)									(0.211)
in-migration in the top 3%		-0.054								-0.524
		(0.038)								(0.322)
in-migration in the top 10%			-0.048							0.270
			(0.038)							(0.233)
top 1% observations				-0.012						1.514
				(0.123)						(1.171)
top 1% movers					-0.103					-1.657
					(0.141)					(1.226)
right wing government						-0.321				-0.410
						(0.257)				(0.328)
debt per capita							-2.173			-0.935
							(2.327)			(3.237)
log of income in top 1%								-2.721		-1.333
								(1.655)		(2.094)
log of income tax revenues									-0.318	-0.059
									(0.526)	(0.530)
Constant	0.672**	0.765**	0.707**	0.472	0.727	0.571***	0.691*	33.013	1.557	12.561
	(0.286)	(0.287)	(0.275)	(0.737)	(0.469)	(0.188)	(0.338)	(19.831)	(1.921)	(25.302)
Observations	15	15	15	15	15	15	15	15	15	15
R-squared	0.081	0.133	0.109	0.001	0.039	0.107	0.063	0.172	0.027	0.712

This table shows the correlation between a dummy for high tax regions (defined as 1 if tax change is larger than 2 percentage points) and share of in-migration in the top 1% (column 1), 3% (column 2), and top 10% (column 3); the total number of observations (column 4) and movers (column 5); a dummy for right wing regional governments (PP, CC, and CiU; column 6); regional debt per capita (column 7), average income in the top percentile (column 8); and log income tax revenues (column 9). Column 10 uses all variables. All values are for the year prior to the reform: 2010. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Migration Flows of Top 1% – Post-Reform

Destination (To)	Origin (From) Andalucía	Aragón	Asturias	Balears	Canarias	Cantabria	Castilla y León	Castilla	Cataluña	Valenciana	Extremadura	Galicia	Madrid	Murcia	Rioja	Other	TOTAL
Andalucía	0	0	0	4	7	0	1	1	7	3	0	0	14	0	1	1	39
Aragón	1	0	0	1	0	0	0	1	2	1	0	0	0	0	0	0	6
Asturias, Principado de	1	0	0	0	1	0	2	0	0	0	0	0	3	0	0	0	7
Balears, Illes	1	0	0	0	1	0	0	0	3	1	0	0	9	0	0	0	15
Canarias	2	0	1	0	0	0	1	0	3	1	0	1	5	0	0	0	14
Cantabria	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	4
Castilla y León	0	0	0	0	1	1	0	0	3	0	1	4	6	1	0	0	17
Castilla - La Mancha	1	0	0	0	1	0	0	0	0	1	0	0	12	1	0	0	16
Cataluña	4	3	2	7	0	0	1	0	0	8	0	2	11	0	0	4	42
Comunitat Valenciana	2	3	0	2	2	0	1	4	6	0	0	1	4	1	0	0	26
Extremadura	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2
Galicia	1	0	0	0	1	0	0	0	2	0	0	0	2	0	0	0	6
Madrid	25	2	5	6	5	2	15	18	16	11	3	11	0	1	2	8	130
Murcia, Región de	0	0	0	0	0	0	0	1	0	3	0	0	2	0	0	1	7
Rioja, La	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TOTAL	39	9	8	20	19	3	21	25	44	29	4	19	69	4	3	15	331

This table shows the pairwise number of migrants by state pairs for moves in the top 1% of the income distribution in the post-reform era. Multiply by 25 to obtain population level estimates. Individuals moving *from* Navarre and the Basque Country are included in the analysis in the "other" column, but individuals moving *to* these regions are not included because they operate independent fiscal systems.

Table A.4: Migration Flows of Top 1% – Pre-Reform

		Origin (From)																
		Andalucía	Aragón	Asturias	Balears	Canarias	Cantabria	Castilla y León	Castilla	Cataluña	Valenciana	Extremadura	Galicia	Madrid	Murcia	Rioja	Other	TOTAL
Destination (To)	Andalucía	0	1	0	1	2	1	1	0	8	8	1	0	17	1	0	4	45
	Aragón	0	0	0	1	0	0	3	1	5	4	0	0	5	0	0	1	20
	Asturias, Principado de	1	0	0	1	1	0	3	0	1	1	1	2	4	0	0	0	15
	Balears, Illes	0	1	0	0	1	0	0	1	10	5	0	1	10	1	0	0	30
	Canarias	3	0	1	2	0	0	0	1	4	1	0	1	6	1	0	1	21
	Cantabria	1	0	0	0	0	0	2	0	0	1	0	1	2	0	1	1	9
	Castilla y León	4	0	0	0	0	0	0	0	0	1	2	1	15	0	0	1	24
	Castilla - La Mancha	4	1	0	1	1	1	3	0	1	1	0	0	50	0	0	1	64
	Cataluña	6	6	3	10	4	1	1	0	0	8	0	2	12	2	0	2	57
	Comunitat Valenciana	5	1	1	2	3	1	1	2	8	0	0	2	20	6	0	0	52
	Extremadura	2	1	1	0	0	0	2	0	2	0	0	0	3	0	0	0	11
	Galicia	1	0	1	0	2	0	3	2	0	2	0	0	6	2	0	1	20
	Madrid	20	9	6	6	12	2	13	36	25	14	7	8	0	5	0	15	178
	Murcia, Región de	1	0	0	0	0	0	0	1	0	5	0	1	5	0	0	0	13
	Rioja, La	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	3
	TOTAL	48	20	13	24	26	7	32	44	65	51	11	19	155	18	1	28	562

This table shows the pairwise number of migrants by state pairs for moves in the top 1% of the income distribution in the pre-reform era. Multiply by 25 to obtain population level estimates. Individuals moving from Navarre and the Basque Country are included in the analysis in the "other" column, but individuals moving to these regions are not included because they operate independent fiscal systems.

Table A.5: Variables for Tax Calculator

variable name	explanation
id	unique id variable
year	year identifier
income	sum of total income of labor tax base
ym_birth	year and month of birth [YYYYMM]
pers_kids_total	total kids in household
pers_kids_0to3	# kids below age 3
pers_elderly_total	total elderly people in household
pers_elderly_75	# of elderly people over age 75
pers_handicap	handicapped household members
pers_elderly_handicap_33to65	# elderly people with handicap of degree 33-65
pers_elderly_handicap_33to65_2	# elderly people with handicap of degree 33-65 and reduced mobility
pers_elderly_handicap_65	# elderly people with handicap of degree 66 and higher
pers_kids_handicap_33to65	# elderly people with handicap of degree 33-65
pers_kids_handicap_33to65_2	# kids people with handicap of degree 33-65 and reduced mobility
pers_kids_handicap_65	# kids people with handicap of degree 66 and higher

Table A.6: Output from Tax Calculator

variable name	explanation
atr_state1	average tax rate of individual in Andalusia
mtr_state1	marginal tax rate of individual in Andalusia
atr_state2	average tax rate of individual in Aragon
mtr_state2	marginal tax rate of individual in Aragon
atr_state3	average tax rate of individual in Asturia
mtr_state3	marginal tax rate of individual in Asturia
atr_state4	average tax rate of individual in Islas Balears
mtr_state4	marginal tax rate of individual in Islas Balears
atr_state5	average tax rate of individual in Canarias
mtr_state5	marginal tax rate of individual in Canarias
atr_state6	average tax rate of individual in Cantabria
mtr_state6	marginal tax rate of individual in Cantabria
atr_state7	average tax rate of individual in Castilla y Leon
mtr_state7	marginal tax rate of individual in Castilla y Leon
atr_state8	average tax rate of individual in Castilla la Mancha
mtr_state8	marginal tax rate of individual in Castilla la Mancha
atr_state9	average tax rate of individual in Catalunya
mtr_state9	marginal tax rate of individual in Catalunya
atr_state10	average tax rate of individual in Valencia
mtr_state10	marginal tax rate of individual in Valencia
atr_state11	average tax rate of individual in Extremadura
mtr_state11	marginal tax rate of individual in Extremadura
atr_state12	average tax rate of individual in Galicia
mtr_state12	marginal tax rate of individual in Galicia
atr_state13	average tax rate of individual in Madrid
mtr_state13	marginal tax rate of individual in Madrid
atr_state14	average tax rate of individual in Murcia
mtr_state14	marginal tax rate of individual in Murcia
atr_state17	average tax rate of individual in La Rioja
mtr_state17	marginal tax rate of individual in La Rioja
atr_state99	average tax rate for individual if region mimicked central government tax
mtr_state99	marginal tax rate for individual if region mimicked central government tax

Table A.7: Tax Rates for a Taxpayer with Income of 300,000 Euro and One Child

	AVERAGE TAX RATES															
year	atr_state1	atr_state2	atr_state3	atr_state4	atr_state5	atr_state6	atr_state7	atr_state8	atr_state9	atr_state10	atr_state11	atr_state12	atr_state13	atr_state14	atr_state17	atr_state99
2005	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17	42.17
2006	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12	42.12
2007	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.35	40.22	40.35	40.35	40.35
2008	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.27	40.29	40.29	40.17	40.29	40.17	40.29
2009	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.25	40.29	40.29	40.17	40.27	40.17	40.29
2010	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.29	40.27	40.29	40.29	40.17	40.29	40.17	40.29
2011	43.31	41.31	43.48	41.31	41.31	43.33	41.31	41.31	43.34	41.28	43.34	41.31	41.18	42.33	41.18	42.33
2012	48.75	45.95	48.12	45.95	46.84	47.97	45.95	45.95	47.99	46.97	47.99	45.95	45.82	46.97	45.82	46.97
2013	48.75	45.95	48.68	45.95	46.84	47.97	45.95	45.95	47.99	46.97	48.00	45.95	45.82	47.57	45.82	46.97
2014	48.75	45.95	48.68	45.95	46.84	48.27	45.95	45.91	47.99	46.94	48.00	45.95	45.43	47.57	45.82	46.97
	MARGINAL TAX RATES															
2005	mtr_state1	mtr_state2	mtr_state3	mtr_state4	mtr_state5	mtr_state6	mtr_state7	mtr_state8	mtr_state9	mtr_state10	mtr_state11	mtr_state12	mtr_state13	mtr_state14	mtr_state17	mtr_state99
2006	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45
2007	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45	45
2008	43	43	43	43	43	43	43	43	43	43	43	43	42.9	43	43	43
2009	43	43	43	43	43	43	43	43	43	42.98	43	43	42.9	43	42.9	43
2010	43	43	43	43	43	43	43	43	43	42.98	43	43	42.9	42.98	42.9	43
2011	43	43	43	43	43	43	43	43	43	42.98	43	43	42.9	43	42.9	43
2012	48	45	48.5	45	45	48	45	45	49	44.98	48	45	44.9	47	44.9	47
2013	55	51	54.5	51	52.08	54	51	51	55	53	54	51	50.9	53	50.9	53
2014	55	51	55	51	52.08	54	51	51	55	53	54	51	50.9	54	50.9	53
	55	51	55	51	52.08	54.5	51	51	55	52.98	54	51	50.5	54	50.9	53

Table A.8: Summary Statistics

variable	income group	pre-reform (<2007)	pre-reform (<2011)	post-reform (>2010)
P(move)	Top 1%	0.012	0.012	0.009
		(0.110)	(0.109)	(0.093)
P(move)	Top 2%	0.010	0.011	0.009
		(0.101)	(0.102)	(0.096)
income	Top 1%	207,202	202,216	176,370
		(364,750)	(270,380)	(226,949)
income	Top 2%	71,123	79,657	79,169
		(5487)	(7915)	(6749)
ATR	Top 1%	37.767	37.166	39.546
		(3.110)	(2.429)	(3.855)
ATR	Top 2%	31.941	32.379	33.944
		(1.404)	(1.263)	(1.639)
MTR	Top 1%	45.000	43.372	48.150
		(0.000)	(0.814)	(3.108)
MTR	Top 2%	45.000	43.358	46.137
		(0.000)	(0.798)	(1.833)

This table shows summary means by income group in the pre- and post-reform period. Standard deviations are in ( ).

Table A.9: Aggregate Analysis of Stock: Formal Dif-in-Dif

	(1) Binary Treatment	(2)
Net-of-tax treatment	0.0162*	0.0122*
	(0.009)	(0.007)
Control for Trends?	N	Y
Number of Observations	1050	1050

The dependent variable is the log ratio of the populations in the top 1% in region d relative to the population in region o. Columns (1) and (2) define a binary treatment that equals one if region d increased its net-of-tax rate relative to region o. Column (2) controls for the time since treatment. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Differences Between Movers and Stayers in Post-Reform Period

variable	Movers	Stayers	Difference	P-value of Mean Difference
pre-move income	137,011	144,253	7241	0.302
	(126,609)	(172,741)		
age	49.028	44.652	-4.375	0.000
	(8.980)	(9.673)		
edu	0.399	0.673	0.275	0.000
	(0.489)	(0.469)		
gender	0.831	0.821	-0.010	0.622
	(0.373)	(0.383)		
kids	0.670	0.695	0.025	0.653
	(1.021)	(1.090)		
atr	39.577	39.546	-0.031	0.874
	(3.613)	(3.854)		

This table shows summary means by movers and stayers and conducts a test of differences in means. The table shows means with standard deviations in ().

Table A.11: Baseline Individual Analysis for Full Sample

	(1)	(2)	(3)
$ln(1 - atr_{i,t,j})$	0.076	0.674	0.513
	(0.079)	(0.423)	(0.686)
individual fixed dummies	Y	Y	Y
j by year dummies	Y	Y	Y
j by education	Y	Y	Y
j by age	Y	Y	Y
j by age squared	Y	Y	Y
j by male	Y	Y	Y
controls	Y	Y	Y
observations	1,439,130	22,815	9,420
number people	95,942	1,521	628

The dependent variable equals one if the region is selected. The independent variable of interest is the log of the net of tax rate where the *person-specific* average tax rate is used and instrumented for using the person-specific marginal tax rate. Column (1) uses all movers and stayers in the top 1%. Column (2) focuses on only movers but includes both movers across regional lines and movers within regions. Column (3) studies movers within a region. We are unable to determine moves within the same municipality or when municipality code information is not available. We omit the region of origin dummy and distance from the controls because it almost perfectly explains location choices when including stayers. All standard errors are clustered two-ways: region-year clusters and move (i,t) clusters. *** p<0.01, ** p<0.05, * p<0.1

Table A.12: Treatment of Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(1 - atr_{i,t,j})$	1.731**	1.731**	1.731**	1.731*	1.731*	1.731**	1.731**	1.731**	1.731**
	(0.713)	(0.816)	(0.809)	(0.952)	(0.952)	(0.797)	(0.835)	(0.835)	(0.837)
SE's	no cluster	individual	move	destination region	destination & move	destination by year	province	province & move	bootstrap
observations	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395
number of moves	893	893	893	893	893	893	893	893	893

This table shows various forms of clustering for the baseline specification given in column 7 of table 3. Column (1) does not cluster. Column 2 clusters over the individual (if an individual moves twice, both moves are in the same cluster). Column (3) clusters over the move (if an individual moves twice, each move in different clusters). Column (4) clusters over destination. Column (5) clusters over the move and destination. Column (6) clusters over destination by year. Column (7) clusters over the province. Column (8) clusters over the province and move. Column (9) bootstraps the standard errors. *** p<0.01, ** p<0.05, * p<0.1

Table A.13: Individual Analysis: Marginal Tax Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1 - mtr_{i,t,j})$	0.569	0.604**	0.670**	0.592*	0.631**	0.602**	0.677**
	(0.367)	(0.305)	(0.305)	(0.305)	(0.306)	(0.304)	(0.308)
place of origin		-0.797***	-0.765***	-0.797***	-0.796***	-0.797***	-0.766***
		(0.061)	(0.060)	(0.061)	(0.061)	(0.061)	(0.060)
place of birth		0.207***	0.206***	0.207***	0.207***	0.207***	0.206***
		(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)
place of first work		0.186***	0.177***	0.186***	0.186***	0.185***	0.177***
		(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)
work place		0.288***	0.260***	0.288***	0.286***	0.287***	0.261***
		(0.018)	(0.021)	(0.018)	(0.018)	(0.018)	(0.021)
ln(distance)		-0.075***	-0.072***	-0.075***	-0.075***	-0.075***	-0.072***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
individual dummies	Y	Y	Y	Y	Y	Y	Y
j by year dummies	Y	Y	Y	Y	Y	Y	Y
j by education	N	N	Y	N	N	N	Y
j by age	N	N	N	Y	Y	N	Y
j by age squared	N	N	N	N	Y	N	Y
j by male	N	N	N	N	N	Y	Y
controls	N	Y	Y	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395	13,395	13,395	13,395
number moves	893	893	893	893	893	893	893
R^2	0.123	0.278	0.302	0.279	0.280	0.279	0.305

In all specifications the estimating sample uses pre- and post-reform moves in the top 1% of the income distribution. Each move has fifteen observations: one for each possible alternative region. The dependent variable equals one if the region is selected. The independent variable of interest is the log of the net of tax rate where the *person specific* marginal tax rate is used. All standard errors are clustered two-ways: region-year clusters and individual move (i, t) clusters. *** p<0.01, ** p<0.05, * p<0.1

Table A.14: IV Robustness Checks: Fixed Brackets

	(1)	(2)	(3)
$ln(1 - atr_{i,t,j})$	1.782**	1.864**	3.734***
	(0.896)	(0.871)	(1.277)
individual dummies	Y	Y	Y
j by year dummies	Y	Y	Y
$\zeta_j \mathbf{x}_{i,t}$	Y	Y	Y
controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y
observations	12,255	10,620	8,040
number of moves	817	708	536
F-statistic	781.3	628	235.2

This table shows the results restricting the sample of moves that are more than 1% away from the nearest bracket threshold (column 1), 2.5% away from the nearest bracket threshold (column 2) and 5% away from the nearest bracket threshold (column 3). All standard errors are clustered two-ways: region-year clusters and move (i, t) clusters. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

Table A.15: Heterogeneity of Effects by Job Characteristics

$ln(1-atr_{i,t,j})$	(1)	(1')	(2)	(3)
Not Fired	2.052***	2.015***		
	(0.789)	(0.778)		
Fired	-0.258	0.847		
	(1.077)	(1.061)		
No Firm Location Change			1.732**	
			(0.796)	
Firm Location Change			1.716	
			(1.491)	
No Contract Change				1.660**
				(0.797)
Contract Change				2.429**
				(1.015)
individual dummies, j by year dummies, $\zeta_j \mathbf{x}_{i,t}$, and controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395
number of moves	893	893	893	893
F-statistic	611.8	496.3	656.8	575.9

The tax rate is interacted with an indicator variable for the group category. This table presents results for the average tax rate. We instrument for the net of average tax rate using the net of marginal tax rate for the individual. The interaction term is instrumented for using the instrument interacted with the indicator variable for the group. Fired / not fired means that the variable is equal to 1 if the individual had a "non-voluntary stop of contract" on the main contract. Column (1) is fired in the year prior to moving and column (1') is fired in the year of moving. Firm location change / no location change is equal to 1 if the headquarter of the firm of the main contract changes but the individual does not change firms in the year of moving. Contract change / no change is equal to 1 if the individual changes the firm of their main contract in the year of move. All standard errors are clustered two-ways: region-year clusters and move (i,t) clusters. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

Table A.16: Individual Analysis: Nonlinear Model

	(1)	(2)
$ln(1-\tau_{i,t,j})$	20.795**	16.579***
	(8.889)	(5.676)
place of origin	-31.259***	-30.354***
	(0.915)	(0.913)
place of birth	2.010***	2.008***
	(0.160)	(0.159)
place of first work	1.748***	1.763***
	(0.155)	(0.154)
work place	2.461***	2.452***
	(0.191)	(0.191)
ln(distance)	-1.343***	-1.342***
	(0.131)	(0.131)
individual dummies	Y	Y
j by year dummies	Y	Y
j by education	Y	Y
j by age	Y	Y
j by age squared	Y	Y
j by male	Y	Y
controls	Y	Y
observations	13,395	13,395
number of moves	893	893

We estimate this model using an alternative-specific conditional logit. In all specifications the estimating sample is restricted to moves in the top 1% of the income distribution. Each move has fifteen observations: one for each possible alternative region. The dependent variable equals one if the region is selected. This table uses the person's average net of tax rate in each region as the independent variable in column (1) and the person's marginal net of tax rate in each region in column (2). All standard errors are clustered at the region-year level. This table presents results using a nonlinear model. *** p<0.01, ** p<0.05, * p<0.1

Table A.17: Occupation Composition of Movers

Occupation	Movers	Percent of Movers	Total in Top 1%	Percent of Total That Move
Engineers, college graduates	160	48.34	15,102	1.06
Managers and graduate assistants	83	25.08	5,338	1.55
Self-employed	55	16.62	14,247	0.39
Others	33	9.97	3,857	0.86

This table gives the occupation breakdown of movers in the top 1%. This table gives the occupation breakdown of movers in the top 1%. Engineers, college graduates includes the highest occupation category in the dataset (ingenieros, licenciados y alta dirrección), managers and graduate assistants include the next two categories (ingenieros técnicos, peritos, y ayudantes) and other includes all lower categories.

Table A.18: Industry Composition of Movers

Industry	Movers	Percent of Movers	Total in Top 1%	Percent of Total That Move
Monetary intermediation	37	11.18	2964	1.25
Freight transport by road and removal services	20	6.04	3546	0.56
Support activities for transportation	19	5.74	749	2.54
Sports activities	17	5.14	199	8.54
#N/A	12	3.63	1725	0.70
Hospital activities	12	3.63	2265	0.53
Passenger transport by air	10	3.02	517	1.93
Medical and dental practice activities	10	3.02	608	1.64
Electric power generation, transmission and distribution	9	2.72	537	1.68
Accounting, book-keeping and auditing activities; tax consultancy	9	2.72	904	1.00
Wholesale of household goods	7	2.11	1065	0.66
Legal activities	7	2.11	656	1.07
Construction of residential and non-residential buildings	6	1.81	556	1.08
Computer programming, consultancy and related activities	6	1.81	824	0.73
Advertising	6	1.81	364	1.65
Manufacture of pharmaceutical specialties	5	1.51	373	1.34
Wholesale of other machinery, equipment and supplies	5	1.51	337	1.48
Hotels and similar accommodation	5	1.51	108	4.63
Activities auxiliary to financial services, except insurance and pension funding	5	1.51	172	2.91
Architectural and engineering activities and related technical consultancy	5	1.51	563	0.89
Publishing of books, periodicals and other publishing activities	4	1.21	223	1.79
Cable telecommunications	4	1.21	380	1.05
All other 3-digit industries	111	33.38	11,768	0.94

This table gives the industry breakdown of movers in the top 1%. The table omits industries that had less than 4 movers in our sample and lumps them into the other category. Regressions using industry utilize a higher level of industry code aggregation than this table.

Table A.19: Heterogeneity of Effects by Occupation

$ln(1 - atr_{i,t,j})$	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(5)
Self-Employed	2.953***	2.953***						2.913***
	(1.021)	(1.021)						(1.024)
Not Self-Employed	1.379*	1.379*						
	(0.836)	(0.836)						
Engineers, college graduates and senior managers			1.645**	1.916**				1.557**
			(0.780)	(0.837)				(0.792)
Not...			1.838*	1.651				
			(0.941)	(1.275)				
Technical engineers and managers, graduate assistants, administrative managers					1.048	0.820		0.995
					(1.281)	(2.627)		(1.277)
Not...					1.883**	0.171		
					(0.794)	(2.869)		
Other							0.924	0.883
							(1.643)	(1.630)
Not Other							1.765**	
							(0.789)	
individual dummies, j by year dummies, $\zeta_j \mathbf{x}_{i,t}$, and controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y	Y	Y	Y	Y	
observations	13,395	13,395	13,395	10,725	13,395	4,020	13,395	13,395
number of moves	893	893	893	715	893	268	893	893
F Statistic	152.3	152.3	368.9	341.4	151.4	140.7	144.5	90.93

The net-of-tax rate is interacted with an indicator variable for the occupation category. In columns (1)-(4) without a prime, we show the effects for the category listed in a row relative to all other observations. In columns with a prime, we show the effect for the category listed relative to all other occupations not given in the rows above. For example, in column (2) we focus on engineers, college grads and senior managers relative to all other occupations including the self-employed. But, in column (2') all other occupations excludes the self-employed. This table presents results for the average tax rate. We instrument for the net of average tax rate using the net of marginal tax rate for the individual. The interaction term is instrumented for using the instrument interacted with the indicator variable for the group. The "other" category includes all occupations not in the previous three groups. Given this is the residual category, we do not have a column (4'). Column (5) includes all occupation interactions in a single regression. All standard errors are clustered two-ways: region-year clusters and individual clusters. We present the Kleibergen-Paap rk Wald F statistic as a test of instrument strength. *** p<0.01, ** p<0.05, * p<0.1

Table A.20: Heterogeneity of Effects by Industry

$ln(1 - atr_{i,t,j})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	Industry k versus All Other Industries																
Industry k	1.200	1.390	-2.850	2.571	1.677	1.418	-2.311	3.605**	1.928**	5.140**	1.747*	1.204	2.115	6.433***	1.411	1.576	5.558*
	(1.752)	(1.364)	(3.390)	(1.899)	(1.270)	(0.960)	(3.735)	(1.749)	(0.864)	(2.359)	(1.053)	(1.724)	(4.503)	(2.280)	(1.107)	(3.330)	(2.864)
Not Industry k	1.761**	1.764**	1.773**	1.711**	1.735**	1.808**	1.756**	1.640**	1.682**	1.724**	1.729**	1.750**	1.731**	1.752**	1.787**	1.733**	1.727**
	(0.799)	(0.793)	(0.798)	(0.791)	(0.802)	(0.822)	(0.794)	(0.793)	(0.811)	(0.797)	(0.837)	(0.810)	(0.799)	(0.806)	(0.855)	(0.794)	(0.796)
	Coefficients from a Single Regression With Taxes Interacted With a Dummies for Each Industry																
Single Regression	1.284	1.542	-2.581	2.748	1.819	1.507	-2.118	3.774**	2.087**	5.487**	1.938*	1.359	2.357	6.445***	1.454	1.669	5.941**
	(1.762)	(1.413)	(3.500)	(1.862)	(1.350)	(1.029)	(3.818)	(1.802)	(0.932)	(2.389)	(1.131)	(1.740)	(4.803)	(2.357)	(1.121)	(3.365)	(2.786)
Short Industry Description	Agriculture	Manufacturing	Electricity	Construction	Wholesale/Retail	Transportation	Tourism	Information	Financial	Real Estate	Professional/Scientific	Administrative	Education	Health	Arts/Entertainment	Extraterrioterial Activities	Other
individual dummies, j by year dummies, $\mathbf{x}_{i,t} \times \iota_j$, and controls: $\mathbf{z}_{i,t,j}$	Y	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y	Y	Y	Y	Y
observations	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395	13,395
number of moves	893	893	893	893	893	893	893	893	893	893	893	893	893	893	893	893	893

The net of tax rate is interacted with an indicator variable for the industry category. In the upper panel, we show the effects for the category listed in a row relative to all other industries. In the second panel, we show a single model estimating all the effects for each industry; thus the row in the second panel represents a single regression. This table presents results for the average tax rate. We instrument for the net of average tax rate using the net of marginal tax rate for the individual. The interaction term is instrumented for using the instrument interacted with the indicator variable for the group. Detail industry categories are (1) Agriculture, forestry, and fishing, (2) Manufacturing, (3) Electricity, gas, steam, and air conditioning supply, (4) Construction, (5) Wholesale and retail trade, repair of motor vehicles and motorcycles; accommodation and food service activities, (6) Transportation and storage, (7) Accommodation and food service activities (8) Information and communication, (9) Financial and insurance activities (10) Real estate activities, (11) Professional, scientific, and technical activities, (12) Administrative and support service activities, (13) Education, (14), Human health and social work activities, (15) Arts, entertainment, and recreation, (16) Activities of extraterritorial organizations and bodies, and (17) Other, which includes all other industry codes that have only a small number of observations including water supply, sewage, waste management and remediation activities; and public administration and defense; compulsory social security. All standard errors are clustered two-ways: region-year clusters and individual clusters. *** p < 0.01, ** p < 0.05, * p < 0.1

Table A.21: Revenue Changes in Thousands of Euros Relative to Mimicking Central Government, Income Above 90,000 Euros

Revenue Change	(1) Mechanical	(2) Income	(3) Mobility	(4) Total	(5) percent
Andalucía	48460	-4418	-9461	34581	.817
		[-4641,-4194]	[-19998,1138]	[24045,45185]	[.568,1.068]
Aragón	-2117	201	415	-1502	-.133
		[176,225]	[-46,874]	[-1963,-1043]	[-.173,-.092]
Asturias, Principado de	8362	-872	-1620	5871	.66
		[-1027,-716]	[-3424,188]	[4058,7683]	[.456,.864]
Balears, Illes	-1216	139	238	-839	-.102
		[119,159]	[-27,505]	[-1104,-571]	[-.135,-.07]
Canarias	2456	-242	-477	1737	.155
		[-276,-208]	[-1009,56]	[1203,2272]	[.107,.203]
Cantabria	1778	-211	-343	1224	.265
		[-263,-158]	[-725,39]	[838,1609]	[.181,.348]
Castilla y León	-2812	300	548	-1963	-.109
		[276,324]	[-66,1160]	[-2579,-1351]	[-.144,-.075]
Castilla - La Mancha	-2599	234	507	-1858	-.167
		[211,257]	[-59,1071]	[-2426,-1294]	[-.218,-.116]
Cataluña	11700	-1220	-2278	8202	.11
		[-1272,-1169]	[-4813,268]	[5665,10748]	[.076,.144]
Comunitat Valenciana	0	0	0	0	0
Extremadura	3916	-414	-756	2746	.551
		[-468,-360]	[-1599,90]	[1901,3592]	[.381,.72]
Galicia	-3126	288	610	-2229	-.123
		[262,313]	[-71,1289]	[-2910,-1550]	[-.161,-.086]
Madrid, Comunidad de	-49030	4226	9482	-35322	-.422
		[4064,4389]	[-1113,19997]	[-45922,-24820]	[-.548,-.296]
Murcia, Región de	1368	-125	-269	973	.127
		[-143,-108]	[-571,32]	[671,1275]	[.087,.166]
Rioja, La	-335	34	64	-236	-.097
		[26,43]	[-7,136]	[-308,-163]	[-.126,-.067]

This table calculates the changes in revenue – in thousands of Euros – realized by the region not mimicking the central government "top" tax rate and assuming the federal tax rate did not change. We define the top tax rate as the effective marginal rate on income above 90,000 Euro (the top 1% threshold, approximately). Column (1) shows the mechanical effect; there are no confidence bands because no parameters are estimated to derive it. Column (2) shows the taxable income response. Column (3) shows the mobility response. Column (4) shows the total change in revenue given by (10). Column (5) shows the total change in revenue as a percent of regional revenue raised from the personal income tax (across all taxpayers). In all columns, we estimate the Pareto parameter for each region using the top 1% of the income distribution in Spain. We use our estimated mobility elasticity and standard error and assume the elasticity of taxable income is 0.15. We present the change in revenue along with a 95% confidence interval, which is obtained using the parametric bootstrap.