# Tax progressivity and RD employment

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**Abstract**

We study the relationship between tax progressivity and the size of the R&D workforce, using a panel of European countries in 2000-2019. We review the theoretical literature which provides opposing predictions about such a relationship. We then demonstrate that such relationship exists as a "within" effect, it is negative, meaning that a larger tax progressivity is associated with smaller shares of employment in R&D activities, and it remains statistically significant after performing a number of robustness tests. Differently to previous studies based on patenting inventors, we find no effect due to top tax rates on the size of R&D employment.

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*Keywords:* Tax progressivity, R&D, Labour force structure.

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# 1 Introduction

Innovation is an important driver of economic growth. Innovation is mostly, albeit not exclusively, the outcome of investments in research and development (R&D) activities and according to the available data, most of R&D spending is for personnel such as scientists and technicians (OECD 2015 figures suggest that on average, 60% of R&D expenditures are for personnel). Thus, any change that policy causes in the supply of R&D work may significantly affect total investment costs for R&D and, therefore, aggregate innovation. Taxes, in particular, are able to affect the innovative output of a country by changing relative prices along multiple behavioural margins, e.g. the choices of how much to work, where to work, in which occupations and on which specific job tasks. In order to make the following discussion more systematic, we identify here three main channels through which income taxes may affect R&D employment: an intensive margin, a location margin, and an extensive margin.

The intensive margin, in the context of R&D work, means not only how much effort a worker puts into the job, but also the risk-taking behaviour that in turn affects the degree of novelty of the potentially successful innovation stemming from the R&D endeavour. Previous studies have shown that payment schemes and complex interactions between taxes and payment schemes are able to affect such behavioural margins, see Manso (2011) for a formal model showing how different payment scheme designs may affect innovative activity. More specifically on the interaction between taxation and payment schemes for innovative employees, d'Andria (2016a) and d'Andria and Savin (2018) propose theoretical models where different tax mixes may affect incentives to commit to more innovative versus safer job tasks. While potentially an important channel per se, the present paper does not study this kind of behavioral effects.

The geographical location choices of inventors and technical workers can be affected by taxation, too, if different jurisdictions enjoy some degree of autonomy over setting tax rates and tax base definitions. An established strand of the literature tries to estimate such effects, see e.g. Moretti and Wilson (2017) and Akcigit, Baslandze, and Stantcheva (2016). High tax rates, both at the personal and corporate level, are found to deter the residence of innovators in favour of lower-tax jurisdictions. The latter seems particularly true for "star" scientists. In this paper we indirectly look at the possibility that top tax rates may provide further incentive to top scientists to leave the country and move to jurisdictions offering lower taxes.

Finally the extensive margin, which is the main focus of this paper, means that workers can decide to enter or to leave the R&D workforce, at a given point in time. The decision, in most cases, is evaluated against an opportunity cost given by alternative uses of one's own time and effort, most notably as employees in jobs that are not related to R&D. The majority of the research in this area concentrates on demand-side effects, e.g. those due to tax credits and subsidies for R&D and how they affect R&D employees' wages (e.g. Goolsbee 1998, Goolsbee 2003, Lokshin and Mohnen 2013), or employment (e.g. Guceri 2018) or the amount of R&D spending (see e.g. Hall and Van Reenen 2000, Dimos and Pugh 2016, d'Andria, Pontikakis, and Skonieczna 2018 and the literature reviews therein). A strand of the literature looks at innovative entrepreneurs and how taxes shape their entry decisions (Keuschnigg and Nielsen 2004, Gentry and Hubbard 2005, Cullen and Gordon 2006). Similarly to R&D employees, entrepreneurs who are potentially innovative also evaluate their entry choice against alternative options: to work as employees, or as non-innovative entrepreneurs. The tax schedule for personal as well as capital income may alter relative prices, which in the context of entrepreneurial entry decisions are net wages and net returns to investment, consequently changing the monetary incentives and risk-reward profiles faced by potential entrepreneurs.

This paper specifically studies how personal income tax policy affects employees entry into, and exit from, the R&D workforce. A notable paper which is to some extent close to ours is Akcigit et al. (2018). In Akcigit et al. (2018) the authors provide estimates, among others, of the effect of top personal marginal tax rates on the number of inventors located in U.S. states, also looking at a long time horizon (thanks to long time series data starting from 1940). One of the main findings is that a larger marginal tax rate is associated with fewer resident inventors. Our contribution differs in at least two ways. First, we look not only at inventors, but at the entire population of R&D personnel. This choice in our view eliminates a confounding factor of the analysis, namely the fact that innovators, defined as those people who successfully managed to apply for at least one patent, are already a selected crowd which excludes not only unsuccessful inventors, but also the potentially very large group of technicians and scientists who are involved in R&D activities but never patent, for a variety of reasons.[1] Also, firms might deem other ways to protect their innovations as more effective than intellectual property rights (IPRs), such as secrecy, lead time and complementary actions as discussed in Cohen, Nelson, and Walsh (2000). The effectiveness of IPRs as a means to protect profit stemming from invention is heterogeneous across industrial sectors and types of R&D (i.e., basic research versus commercial development), thus by looking only at patenting inventors one would likely focus on a sample that provides a biased representation of the general population of inventors.

The second point of departure from Akcigit et al. (2018) is that we are interested here in the effects of tax progressivity rather than solely in the level of tax rates. Intuition would lead to predict that stronger personal tax progressivity is associated with less participation to R&D activities, as the corresponding net return would be reduced for high-income earners (which equates to say, for the most successful innovators). However, one needs to consider that at any point in time agents choose whether to work or not in R&D, by comparing the expected payoff from R&D work against the expected payoff from working in an alternative job, whose wage can also be simultaneously affected by the tax progressivity. The fact alone that tax progressivity may affect both the payoff from R&D work and the opportunity cost from an alternative job already makes the relationship between tax progressivity and aggregate R&D employment non-trivial. For instance, if a worker expects potential upswings in income from the R&D work in case of a successful innovation, then more progressive taxes might imply a reduced expected payoff from R&D work compared to the alternative work option. However, the alternative work option might instead offer higher wages if workers "pay to be scientists" (as hypothesized in Stern 2004), which would imply that stronger progressivity makes R&D work relative more appealing. Thus, even under perfect information the relationship between tax progressivity and R&D employment is function of a number of variables and its sign cannot be easily generalized *ex ante*.

[1] As an example of reasons not to patent, refer to the arguments presented in Calderini, Franzoni, and Vezzulli (2007).

As we will clarify in the next section dedicated to previous findings in the literature, the sign of the relationship between tax progressivity and R&D employment depends on a number of assumptions regarding the informational regime and preferences about scientific work. To provide insight on the matter and guidance as to which of the many possible theoretical frameworks are compatible with empirical evidence, our analysis exploits macro data for 24 European countries in the period 2000 to 2019 and the main findings can be summarized as follows. First, tax progressivity is found to be mostly a "within" effect (in the context of the following analysis, "within" effects are longitudinal effects at the level of countries), while "between" effects (the time-invariant differences between countries) are never found to be statistically significant. Second, the "within" effect is negative, meaning that countries increasing their tax progressivity experience on average a reduction in their shares of R&D employees, after controlling for a number of country-specific characteristics. The sign of this relationship is robust to a number of tests, including using different definitions of tax progressivity. Third, when trying to replicate results from U.S.-based studies reporting a negative correlation between top marginal tax rates and resident innovators, we never find statistically robust coefficients in our sample.

# 2 Previous literature and hypotheses formulation

This section presents empirical results on scientists' wages and summarizes results from several distinct strands of literature, which are relevant to predict what relationship to expect between tax progressivity and the extensive margin in R&D jobs. These results are organized into four theoretical frameworks for an easier exposition and to provide a link to the corresponding theoretical literature. As we are going to demonstrate, different assumptions with respect to preferences and the information regime in the R&D job market may produce radically different predictions.

The first three theoretical frameworks presented in the following subsections predict either a positive or negative correlation between higher tax progressivity and the participation to the R&D workforce. All these theories are based on the idea that agents are presented with a choice of either working in an R&D job, or in an alternative job outside of R&D. For example, one might think of engineers in an R&D position who may opt instead for a managerial position or for another technical job that entails minimal scientific tasks. The last theoretical framework presented hereafter instead points to the possibility that potential R&D workers move out of a country. In the latter case, higher tax liabilities may provide stronger incentives to do so.

All the following theoretical frameworks only look at monetary incentives. It is known (e.g. Sauermann and Cohen 2010) that monetary incentives play a role in the decision-making of employees involved in innovative processes, although other motives can be as important, or even more important. All the theories that follow implicitly assume that such non-pecuniary motives are not affected by pecuniary incentives, thus one can safely assume a *ceteris paribus* condition w.r.t. to such non-pecuniary motives and focus in isolation on the effects of net wages on labour choices.

## 2.1 Scientists' wages

It is quite challenging to get a clear idea of how much R&D workers are paid, due to data limitations in several countries. Even more challenging is to estimate the wage these workers would get, if employed in non-R&D functions. Generally speaking, R&D workers possess on average high educational attainments, often a Ph.D. Data from OECD's Education at a Glance 2021 report that 68% of tertiary-educated adults in OECD countries earn more than the median income for the country, against only 27% for adults with below upper secondary attainment. Full-time workers with tertiary attainments have an earnings advantage of about 57% across OECD countries, compared to those with upper secondary education, and this advantage raises to 95% for those with a master or doctoral degree.

To obtain a more precise estimate one may look at the earnings by scientists. These can somewhat proxy for the wages earned by personnel involved in R&D jobs, though the latter entail also more applied technical tasks, thus strictly speaking, they are not necessarily classifiable as science. Data for the U.S.[2] report the mean annual wage for Life, Physical, and Social Science occupations equal to 79,360 USD, and the median income equal to 69,760 USD. Therefore, with an annual mean wage of 56,310 USD for all occupations in the U.S., these earnings tend to be in the higher half of the income distribution, above the median but not necessarily in the highest tax brackets. However, these figures mask a large degree of heterogeneity. For example the occupational category for Physicists earns a median annual salary of 129,850 USD, thus significantly larger than the median salary for other scientific occupations and much larger than the median for all occupations.

These figures suggest that the relevant tax brackets for R&D employees should be in the upper-half of the income distribution, though one cannot exclude that young scientists pay a significant discount (the latter will be discussed more in depth in the next subsections dealing with informational constraints). This, in turn, implies that higher tax rates for high income earners (and as such, a stronger tax progressivity) should deter some workers to pursue a career in R&D and opt for other career options. We derive the following two hypotheses:

*H0:* tax progressivity is negatively correlated with the share of R&D workers over the total workforce.

*H0a:* the relevant tax progressivity for hypothesis H0 is computed starting from the average income for the country.

Hypothesis H0 provides a testable statement which we will test against alternative hypotheses described in the following subsections. Hypothesis H0a suggests which tax progressivity indicator should be the relevant one to detect such correlations, which will also be useful in the empirical part of the paper when dealing with different definitions of tax progressivity.

[2]These data were collected from the Bureau of Labour Statistics (accessed on 18/9/2021): https://www.bls.gov/oes/current/oes190000.htm

## 2.2 A preference for science

The idea that some intellectual professions may involve acceptance of a lower wage because of preferences (e.g. due to some social return associated to the prestige of a given job) is old and already defended in Adam Smith's The Wealth of Nations. More recently, Stern (2004) applied a similar concept to workers in R&D functions: if these people have a "taste for science" and are willing to forego larger earnings for the possibility to engage in more intellectually enticing tasks, then one would expect that wages in R&D are on average lower than wages obtained in non-R&D functions, for an equal level of human capital. It is important to stress that these workers may usually obtain wages from non-R&D jobs that are above the mean for the country, as the returns to education discussed im previous subsection imply. Thus, when talking about a possible discount for wages in R&D, that discount is calculated relative to above-average wages.

If such theory is correct, then a more pronounced tax progressivity in the appropriate range of incomes would reduce the (higher) wage from non-R&D jobs more than the (lower) wage from R&D jobs, thus making R&D jobs at the margin more appealing. Consequently, the prediction in this case would be that a more progressive tax schedule should, *ceteris paribus*, drive more workers into R&D jobs. The kind of progressivity that would drive the effect is one which does not consider the very extremes of the wage distribution, rather according to the results presented in Stern (2004) the reduction in wages should be relatively small (around 27% reduced wages on average) compared to the full extension of incomes across the tax schedule. This produces the following hypotheses:

*H1:* tax progressivity is positively correlated with the share of R&D workers over the total workforce.

*H1a:* the relevant tax progressivity for hypothesis H1 is computed starting from the average income for the country.

These two new hypotheses may be directly contrasted, respectively, with previous hypotheses H0 and H0a.

## 2.3 Symmetric uncertainty

By symmetric uncertainty we mean a condition where agents themselves are unable to estimate *ex ante* their ability as R&D employees and, hence, their productivity. Models of symmetric uncertainty have been developed at least since Jovanovic (1979) and are closely related to the literature on "bandit" problems, where a trade off occurs between a payoff now and information that may increase payoffs in the future. These models are often used to study markets for talent, that is, job markets for artists, performers, sportsmen, entrepreneurs, and possibly scientists and other workers potentially involved in R&D activities.

In particular here we focus on a model presented in Terviö (2009) and extended in d'Andria (2018) to include personal taxes. In Terviö (2009) novice workers would like to pay an entry price to a talent-driven job market (such price can be in the form of a reduced wage compared to the wage they could obtain from an alternative job option), but they are credit constrained and thus, they are able to accept only so much of a reduction in wage. In the model, novices bear the cost of discovering their own talent, the assumption being that once discovered they can switch job at no cost and earn a higher wage, if found to have high productivity. Thus, this entry price can be thought of as a lottery ticket, where the lottery prize is to be discovered as a highly talented worker. In each period the number of novices is limited compared to a first-best scenario without credit constraints, which causes a shortage of yet-to-be-tested young workers compared to the first-best socially optimal scenario.

The model predicts the following phenomena (as compared to the first-best scenario without credit constraints): first, a reduced number of workers occurs in the talent-driven sector; second, more low-ability workers stay in the talent-driven market (they would otherwise exit the market); third, wages for those workers who are found to be highly talented are larger. In d'Andria (2018) the model is extended to include personal income taxes, and the main finding is that a more progressive tax schedule where the tax rate on novices' wages is smaller than the tax rate on veteran workers in the talent-driven sector, moves the market closer to a first-best scenario. The intuition behind this result is that a larger tax on veterans' wages increases exit of lower-ability mediocrities and raises the entry of novices, while a lower tax rate on entry wages allows the market, at the equilibrium, to accommodate more novices into the talent-driven sector. Overall the model predicts that a more progressive tax schedule entails more workers in the talent-driven sector and that the tax burden on low wages is also relevant as it affects the entry wages of novices.

Taken together these predictions can be summarized in the following hypotheses, where the first is just equal to the one obtained assuming a "taste for science".

*H1:* tax progressivity is positively correlated with the share of R&D workers over the total workforce.

*H1b:* keeping the rest of the tax schedule constant, higher tax rates on low incomes deter entry into R&D jobs, while higher tax rates on high incomes favor entry into R&D jobs.

## 2.4 Asymmetric information

Asymmetric information in the present context means that workers possess better knowledge of their own ability, compared to prospect employers. Workers cannot reliably signal their ability type to employers, thus the latter are only able to offer the same set of contracts to all employees. The classical paper by Weiss (1980) is based on the assumption that reservation wages positively correlate with ability. It shows that workers will be exceedingly drawn from the bottom of the ability distribution and too few will be hired. Firms will keep wages high even if this will cause job queues, as cutting wages would first make the highest-ability workers to exit. In such setting, personal income taxes reduce wages and thus act similarly to a wage cut, reducing the average ability of workers in the sector but allowing for more (low-ability) entrants.

In Weiss (1980) the model is further extended to include the possibility that workers are partitioned into "types". Workers of the same type have the same observable characteristics but different reservation wages and ability. These workers' "types" may thus receive different wages. In the case of R&D workers, observable characteristics might be for example having patented at least once, or having worked for highly regarded companies or institutions. If one further assumes that the ranking of the wages for each type are weakly increasing in the average ability of each group, increasing tax progressivity in this setting would reduce entry more for the highest-ability individuals within each type group and more so for the higher-ability types (similarly to models such as, e.g., Boadway and Sato 2011). Average productivity of the entire sector would fall down, consequently driving down net wages up to a new equilibrium with lower entry, lower gross wages and lower average ability compared to before increasing tax progressivity. Overall these effects would predict the following hypothesis, which is the same as H0 detailed previously:

*H0:* tax progressivity is negatively correlated with the share of R&D workers over the total workforce.

It is the case to highlight that, even accepting by assumption that the job market for scientists is mostly a market with asymmetric information, where scientists can better evaluate their own ability compared to prospect employers, a number of additional assumptions need to be met in order to claim the theoretical prediction of a negative relationship between top tax rates, or tax progressivity, and market entry (e.g. see on topic Boadway and Keen 2006 and d'Andria 2018: although these papers are focused on the link between taxes and entrepreneurial entry rather than on the job market for R&D workers, many of the considerations discussed therein apply to R&D employment as well). Thus, hypothesis *H0* needs to be interpreted not as the predicted outcome of any and all models of R&D job markets with asymmetric information, rather as the outcome of a subset of such models featuring specific assumptions.

### 2.5 International mobility of workers

There is an ample empirical literature showing that elite scientists, particularly the very top or superstar scientists, are highly mobile across countries. Scientists with more publications and who obtained larger funding are found to be more mobile (Azoulay, Ganguli, and Zivin 2017). Taxes are also found to be a factor that co-determines, together with other factors, the location choices of star scientists (Moretti and Wilson 2017).

The intuition behind these empirical results is quite straightforward: elite scientists earn above-average wages, thus a rise in tax rates on the higher tax brackets provides them with an incentive to move to low-tax jurisdictions. Other things staying the same, an increase in top tax rates should then drive more top scientists abroad, thus reducing both the number of scientists in the country and the average productivity of scientists there, which could further drive down wages for scientists and thus their number. Overall these observations lead to the following hypothesis:

*H2:* Higher top tax rates are negatively correlated with the share of R&D workers over the total workforce.

## 3 Methodology and data

The dataset is obtained by combining data from Eurostat and the OECD. It comprises 24 European countries in the years between 2000 and 2019. In the following, the dependent variable is always the share of R&D personnel and researchers in total active population (labelled *R&D workforce*), as published by Eurostat and expressed as percentage points. This statistics measures R&D personnel in full-time equivalent units. The variable is defined by Eurostat as follows: it "consists of all individuals employed directly in the field of research and development (R & D), including persons providing direct services, such as managers, administrators, and clerical staff. A R & D researcher can be employed in the public or the private sector - including academia - to create new knowledge, products, processes and methods, as well as to manage the projects concerned." In the regression models presented hereafter, the R&D workforce variable is expressed in basis points, meaning that a value of 100 represents that 1% of the workforce is employed in R&D jobs.

We employ several country-level controls, taken from Eurostat data. These are: GDP per capita at PPS values, expressed as percentage of the median value across EU28 (*gdp_pc*); resident population expressed in thousands (*population*); tax revenues collected from personal taxation, as a percentage of GDP (*revgdp*); Gross Expenditure for R&D, in million Euros (*GERD*); finally, the number of patent applications to the European Patent Office by priority year (*patents*). Taken together, these variables are meant to control for demand-side characteristics of the labour market for R&D personnel, the degree of innovative productivity (proxied by the number of patents per year) and the general level of taxation levied on labour income. We also include controls for time trends, the methodology and selection of which is detailed in the next section. Note that the inclusion of the *GERD* control variable also indirectly captures the effects of specific policies for R&D, which could provide incentives to hire workers in such functions. It stands to reason that any (tax or subsidy) incentive to R&D spending which indeed produces some additionality (in the meaning used, e.g., in Dimos and Pugh 2016 and d'Andria, Pontikakis, and Skonieczna 2018), will increase *GERD* as well as it includes all spending for R&D by private and public entities.

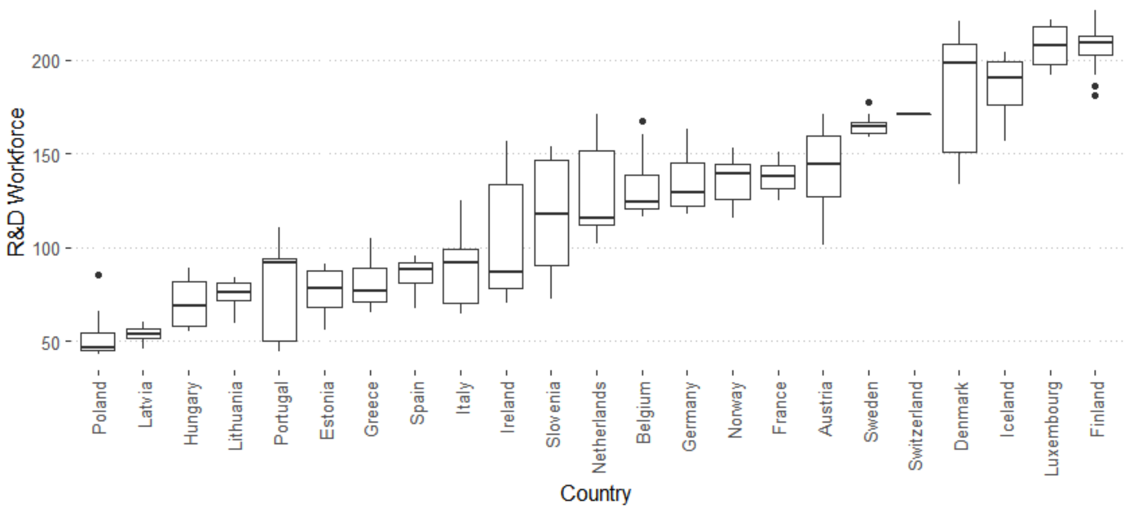
The main regressors of interest are tax rates and measures of tax progressivity derived from them. To this end we employ the OECD Taxing Wages database, in particular we use: the average effective tax rate paid by a household earning the mean income and composed of a single person without children (*AVGTR*); the same tax rate for a two-earner married couple, one at 100% of average earnings and the other at 67%, with two children (*AVGTRcouple*); the same rate computed for a single-person without children, earning 67% (*AVGTRlow*) of the average income; the marginal tax rate for a single-person without children, earning 167% of the average income (*MTR167*); finally, the top statutory personal income tax rate (*TOPTR*).

Our preferred indicator of tax progressivity is the following one:

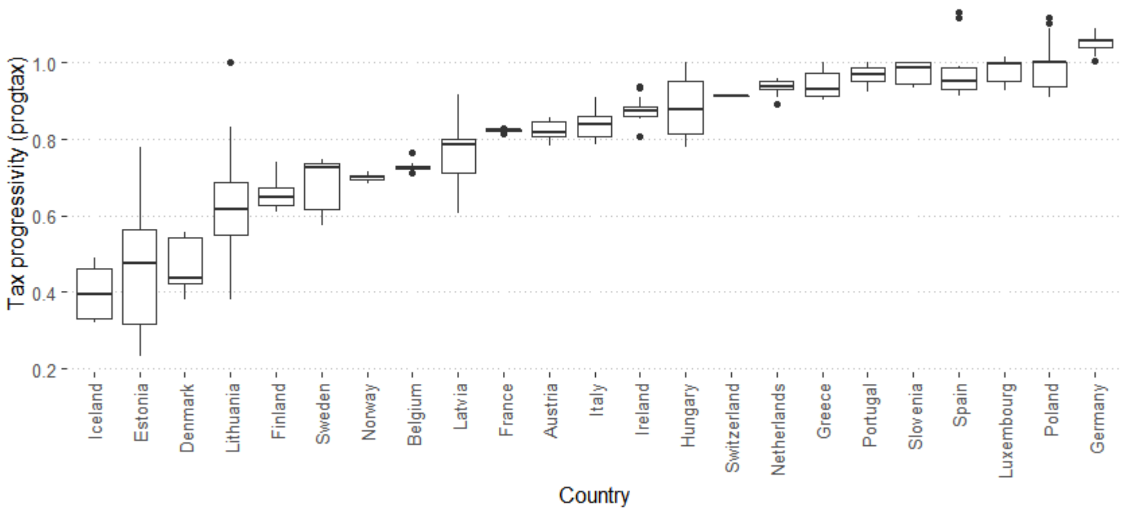
$$\text{progtax} = \frac{\text{MTR167} - \text{AVGTRlow}}{\text{MTR167}} \tag{1}$$

The variable *progtax* described by eq. (2) is used (unless stated otherwise) to produce the results in the following tables. This index captures progressivity globally by computing the difference between the marginal tax rate for high-income earners and the average effective tax rate for low income earners. The difference is then divided by *MTR167* to express it in a more comparable form across countries which is not affected by the size of top rates. Note that the values for *AVGTRlow* (similarly for *AVGTRcouple* and, though less likely, for *AVGTR*) can also be negative, which simply increases the difference at the numerator of eq. (2) and may produce values for *progtax* larger than 1. This indicator captures at the same time the tax rate on low income which is the one that applies to the wages of young scientist, and a tax rate on high (but not necessarily top) income which are, as discussed in previous section, those more likely earned by R&D workers.

Figure 1: Distribution of R&D employment and tax progressivity across countries




(a) Share of R&D personnel over total workforce (100 = 1%)




(b) Tax progressivity index *progtax* (zero = no progressivity)

Figures 1a and 1b show the distribution of our dependent variable and of the progressivity index *progtax* as boxplots, computed across the years (from 2000 to 2019) available in the sample. *R&D workforce* ranges from values as low as 0.43% (for Poland in 2009) up to 2.26% (for Finland in 2004). The progressivity index *progtax* ranges from very low values (e.g. for Iceland and Denmark) up to the highest values observed for Germany. Note again that *progtax* may also be larger than 1, which is the case if the average tax rate on low income *AVGTRlow* is negative (e.g. see Spain and Poland). These graphs are also useful to appreciate the variation observed in both variables during this interval of time, with some countries having basically no change (e.g. Switzerland), while others experienced large swing in either R&D employment (e.g. Ireland, Slovenia, Denmark) or tax progressivity (e.g. Estonia, Lithuania).

For added robustness, we also rerun the same regression models using different specifications of the progressivity index, either using the top statutory rate (*TOPTR*) instead of *MTR167*, or substituting *AVGTRlow* with either *AVGTR* or *AVGTRcouple*. Different definitions of the progressivity index offer a different point of view w.r.t. the kind of entry mechanism to be tested. For instance, our main indicator, *progtax*, compares the (marginal and average) tax rates on high and low incomes, which is the proper indicator if one assumes that R&D jobs are high-income jobs (at least in expectation) while the outside option entails low-income jobs (a likely scenario for young workers at the beginning of their professional careers). Similarly, the choice of using average or marginal tax rates also implies different perspectives on the same job market. We follow the prevalent literature which defines tax progressivity using the difference between a marginal tax rate on higher incomes and a (lower) average tax rate. We believe this is the right approach to the kind of research questions posed here, as R&D activities are able to produce exceptional upswings in value which are somewhat reflected in improved wages of the employees who were more directly involved in the innovative process (see on topic the evidence presented in Toivanen and Väänänen 2012 and Depalo and Di Addario 2015; also refer to the theoretical motivations discussed in d'Andria 2016b). It is reasonable to believe that workers incorporate the expected value of such upswings in their evaluations and thus, marginal tax rates on high incomes are those which would affect the corresponding monetary incentives to enter the R&D job market. This said, it is however the case to note that the distribution of scientists' ability is very skewed, see for example Sinatra et al. (2016). It stands to reason that the very top marginal tax rates would only apply to very few scientist and, thus, in expectation, play only a minor role in affecting entry decisions. This is one reason why we believe that progressivity indicators built using *MTR167* instead of the top tax rates better capture the income range that is relevant for R&D employees.

The four alternative specifications for the progressivity index are the following:

$$\text{progtax1} = \frac{\text{MTR167} - \text{AVGTRlow}}{\text{MTR167}} \tag{2}$$

$$\text{progtax2} = \frac{\text{TOPTR} - \text{AVGTRlow}}{\text{TOPTR}} \tag{3}$$

$$\text{progtax3} = \frac{\text{MTR167} - \text{AVGTR}}{\text{MTR167}} \tag{4}$$

$$\text{progtax4} = \frac{\text{MTR167} - \text{AVGTRcouple}}{\text{MTR167}} \tag{5}$$

The definition of *progtax2* uses the top statutory tax rate instead of the marginal tax rate on the income at 167% of average income. *progtax3* and *progtax4* use the average tax rate, or the average tax rate for married couples, respectively, instead of the average tax rate on low income (as explained, the latter is computed for a single without children, earning 67% of average income). Note that the indexes *progtax3* and *progtax4* measure progressivity in a narrower interval of tax rates that is positioned between mean and high incomes. The latter range should better capture the range of incomes where R&D workers should evaluate their expected wages from R&D and non-R&D jobs, also if the "taste for science" hypothesis holds. The indexes *progtax1* and *progtax2* instead capture progressivity on an ample range of incomes ranging from low to high or very high incomes, and are thus better fit to estimate the kind of relationship predicted by theoretical frameworks based on either symmetric uncertainty or asymmetric information.

All results reported hereafter were obtained in R version 4.1.0 and using RStudio 1.4.1106. All panel models were estimated using the *plm* package (see Croissant and Millo 2008) while "between-within" models were estimated using the *panelr* package (Long 2021). Robust errors are obtained using function *coeftest* from the package *lmtest* (Hothorn et al. 2015). The tables reporting results were obtained using the package *stargazer*, see Hlavac (2018).

# 4 Results

We first run a number of preliminary regression tests in order to better identify the model which best fits our data. Section 4.1 summarizes the procedure we followed to select our main model specification, which produced then the results presented in section 4.2

## 4.1 Preliminary regression tests

Table 1 compares results from a pooled OLS, a fixed-effects model with robust standard errors, and a between-effects model. A Breusch-Pagan test rejects the hypothesis of no significant fixed effects with $p$-value= 0.010. We also ran a "between-within" model[3] which obtained similar results. These preliminary tests point to significant "within" effects while "between" effects are never statistically significant. Therefore in the following we concentrate on fixed-effects models only.

The size of the R&D workforce might be following common trajectories that are beyond just a single year horizon. To test if time trends play a role we experimented with adding either year dummies or a polynomial of an index of the years (where for our initial year, 2000, the index is set to 1) up to the seventeenth degree polynomial. We thus found that a squared time trend provides the best fit. Table 2 shows a comparison of a fixed-effects model without time trend, with a linear and then with a quadratic time trend. In the following we will keep using a quadratic time trend to proceed in the analysis.

We then checked whether the effects happen with some lags. We lagged all independent variables, using alternatively from one to five years lags. The model's fit improves up to 2-year lag and then decreases. Table 3 reports the coefficients for the variable *progtax* only, for the models with one, two and three year lags. Based on these results, in the following we keep using 2-year lagged values. Interestingly the regression model employed in Akcigit et al. (2018) employs three-year lags, so it is quite close to ours. Note that

[3]Also known as "within-between" and "Mundlak" models after the name of their first proponent (Mundlak 1978). We followed Bell and Jones (2015) and defined a model where regressors are included as time-invariant country-specific means to capture the "between effects", and as time-varying differences from such means to capture "within" effects. Results are available upon request.

Table 1: Results from pooled OLS, fixed effects and "between" effects models

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | | *panel models* | |
| | *OLS* | *Fixed effects* | *"Between" effects* |
| | (1) | (2) | (3) |
| progtax | −13.350 | −46.759*** | 8.295 |
| | (9.800) | (11.337) | (56.055) |
| TOPTR | 0.326** | 0.166 | 0.113 |
| | (0.165) | (0.173) | (1.107) |
| revgdp | 0.460 | −0.012 | 1.074 |
| | (0.444) | (0.752) | (2.230) |
| gdp_pc | −0.021 | −0.321*** | −0.048 |
| | (0.033) | (0.063) | (0.193) |
| log(population) | −43.553*** | 53.105*** | −44.877** |
| | (2.426) | (17.373) | (15.396) |
| log(patents) | 0.584 | −9.476*** | 7.272 |
| | (2.300) | (2.775) | (11.192) |
| log(GERD) | 33.986*** | 47.499*** | 26.733 |
| | (3.446) | (2.973) | (21.831) |
| Constant | 229.704*** | | 245.798*** |
| | (13.150) | | (53.311) |
| Observations | 366 | 366 | 23 |
| $R^2$ | 0.820 | 0.581 | 0.889 |
| Adjusted $R^2$ | 0.816 | 0.545 | 0.837 |

*Note: Standard errors in parenthesis.*
*Note: The fixed-effects model is with HC1 robust errors.*
*p<0.1; **p<0.05; ***p<0.01

lagging the independent variables also has the additional advantage of mitigating potential issues related to reverse causality bias (more on the point under section 4.3).

## 4.2 Main results

Armed with the insight from previous section we choose our main specification as a fixed-effects model including a quadratic time trend and using 2-year lagged independent variables. Table 4 summarizes results obtained from our main model (column 1), and by models obtained by substituting the tax progressivity indicator, *progtax*, with one of the alternative specifications detailed previously.

Results from table 4 show that the alternative definitions for the progressivity indicator lose statistical significance when using robust standard errors. Even then, the standard

Table 2: Fixed-effects model: (1) without time trend, (2) with linear time trend, (3) with quadratic time trend

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | (1) | (2) | (3) |
| progtax | $-46.759^{*}$ | $-51.194^{**}$ | $-59.156^{**}$ |
| | (25.621) | (23.888) | (23.681) |
| TOPTR | 0.166 | 0.165 | 0.014 |
| | (0.333) | (0.300) | (0.286) |
| revgdp | $-0.012$ | $-0.004$ | $-0.113$ |
| | (1.175) | (1.147) | (1.074) |
| gdp_pc | $-0.321^{*}$ | $-0.264$ | $-0.311^{**}$ |
| | (0.165) | (0.165) | (0.156) |
| log(population) | 53.105 | 24.777 | 42.931 |
| | (54.248) | (50.427) | (54.613) |
| log(patents) | $-9.476^{**}$ | $-8.894^{**}$ | $-7.040^{**}$ |
| | (3.838) | (3.639) | (3.467) |
| log(GERD) | $47.499^{***}$ | $36.930^{***}$ | $41.563^{***}$ |
| | (7.769) | (10.186) | (10.127) |
| Year | | 0.838 | $-1.672$ |
| | | (0.569) | (1.132) |
| Year (squared) | | | $0.111^{**}$ |
| | | | (0.045) |
| Observations | 366 | 366 | 366 |
| $R^2$ | 0.581 | 0.594 | 0.611 |
| Adjusted $R^2$ | 0.545 | 0.558 | 0.575 |

*Note: HC1 robust standard errors in parenthesis.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

error is always smaller than the absolute value of the obtained coefficient, which indicates that the sign of the relationship between tax progressivity and R&D workforce remains clearly negative. It is interesting also to highlight that the coefficients for $TOPTR$ are always small and never statistically significant.

Taking results from our preferred regression model, an increase of plus one of the *progtax* index would entail approximately a decrease of -0.35 percentage points in the share of R&D workers. To better understand what this magnitude means, consider a country starting from a tax schedule with an average effective tax rate on low incomes of 20% and a marginal tax rate on high incomes of 40%. This would produce a *progtax* index of 0.5. Let us now assume that a policy reform moderately changes these rates to 18% and 45%, respectively. The corresponding progressivity index *progtax* would then increase

Table 3: Fixed effects models with one, two and three years lagged regressors.

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | (1) | (2) | (3) |
| progtax, 1-year lag | −45.241** | | |
| | (19.829) | | |
| progtax, 2-year lag | | −34.705* | |
| | | (18.808) | |
| progtax, 3-year lag | | | −23.343 |
| | | | (19.342) |
| *(controls omitted in table)* | | | |
| Observations | 361 | 346 | 329 |
| $R^2$ | 0.605 | 0.610 | 0.605 |
| Adjusted $R^2$ | 0.569 | 0.573 | 0.566 |

*Note: HC1 robust standard errors in parenthesis.*
*p<0.1; **p<0.05; ***p<0.01

from 0.5 to 0.6, which means that the predicted reduction in R&D employment would be -0.035 percentage points. While that might seem a small variation, consider that the mean value for the *R&D workforce* variable in our data is about 1.18%: in our example, this mean value would decrease to 1.145%, which is not a big change in absolute terms, but quite significant in relative terms. A much larger reform, for example one raising the tax progressivity from 0.5 (as observed in some countries, refer again to Figure 1b) to 1.0, would reduce R&D employment by -0.175 percentage points, thus the mean value would drop from about 1.18% to about 1.0%.

We turn now to individual tax rates to shed light on specific mechanisms as detailed in previous section 2. We omit the progressivity index (as it is built from the variables we intend to employ now as regressors) and use instead the components of such index as main regressors. Table 5 reports results, respectively for a model using the average tax rate on low incomes and the marginal tax rate on high incomes (which are the variables used to build *progtax*), then in column (2) we use the top statutory tax rate in lieu of the marginal tax rate (which are the variables used to build the index *progtax2*), finally in column (3) we use the average tax rate on mean income (which are the variables used to build the index *progtax3*). This alternative set of estimates allows to better understand whether results obtained for the progressivity indexes are especially driven by changes in high or low tax rates, rather than in the overall progressivity. Two results in Table 5 are worth highlighting. First, tax rates on high income are never statistically significant per se and always produce tiny coefficients. This result is incompatible with the idea that the observed reduction in R&D employment due to higher tax progressivity is mostly due to international mobility of elite scientists. Second, tax rates on mean and low incomes produce small, but highly significant positive coefficients. The latter result is not coherent with a theoretical framework featuring symmetric uncertainty, where one would expect

Table 4: Results (fixed-effects model) using different definitions for the index of tax progressivity. Independent variables are lagged 2 years.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | R&D workforce | | | |
| | (1) | (2) | (3) | (4) |
| progtax | $-34.705^{*}$ | | | |
| | (18.808) | | | |
| progtax2 | | $-23.434$ | | |
| | | (17.056) | | |
| progtax3 | | | $-38.293$ | |
| | | | (29.189) | |
| progtax4 | | | | $-41.686$ |
| | | | | (29.581) |
| TOPTR | $-0.120$ | $-0.063$ | $-0.070$ | $-0.085$ |
| | (0.292) | (0.316) | (0.305) | (0.306) |
| revgdp | 1.304 | 1.592 | 1.248 | 1.201 |
| | (1.547) | (1.504) | (1.594) | (1.586) |
| gdp_pc | $-0.498^{**}$ | $-0.505^{**}$ | $-0.503^{**}$ | $-0.504^{**}$ |
| | (0.196) | (0.196) | (0.203) | (0.206) |
| log(population) | 36.328 | 38.302 | 38.997 | 34.163 |
| | (37.828) | (37.553) | (38.768) | (38.823) |
| log(patents) | $-2.484$ | $-3.052$ | $-3.400$ | $-2.650$ |
| | (2.945) | (2.950) | (3.005) | (2.846) |
| log(GERD) | $24.358^{***}$ | $24.181^{***}$ | $23.984^{***}$ | $24.194^{***}$ |
| | (8.544) | (8.649) | (8.649) | (8.644) |
| Year | $-0.651$ | $-0.533$ | $-0.221$ | $-0.304$ |
| | (1.592) | (1.602) | (1.606) | (1.580) |
| Year (squared) | 0.076 | 0.070 | 0.055 | 0.060 |
| | (0.050) | (0.051) | (0.051) | (0.050) |
| Observations | 346 | 346 | 346 | 346 |
| $R^2$ | 0.610 | 0.606 | 0.606 | 0.608 |
| Adjusted $R^2$ | 0.573 | 0.569 | 0.569 | 0.570 |
| F Statistic (df = 9; 315) | $54.757^{***}$ | $53.851^{***}$ | $53.906^{***}$ | $54.203^{***}$ |

*Note: HC1 robust standard errors in parenthesis.*
*All independent variables are 2-year lags.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

the opposite sign (as tax rates on low income affect the wage of novices). It also casts doubts on the plausibility of the "taste for science" hypothesis: to the extent that R&D

wages fall close enough to mean income because of the discount that scientists would pay to be scientists, increases in *AVGTR* should produce negative coefficients, while *MTR167* should produce positive coefficients as Mincerian returns to human capital earned from the outside (non-R&D) alternative job would be reduced.

In summary, we find no support for hypotheses H0a, H1, H1a and H2. Hypothesis H0 is compatible with the results from our empirical estimation. H1b is also per se compatible, but because H1 is not, it only provides limited support to the symmetric uncertainty framework. These results point to asymmetric information as the only theoretical framework that is potentially able to explain said results. The fact that the progressivity measures computed using the tax rates on low income are found to better explain said relationship, suggests that the entry wage into R&D jobs also play a role.

## 4.3 Robustness tests

We perform here a number of additional tests to check the robustness of the main results presented in section 4.2.

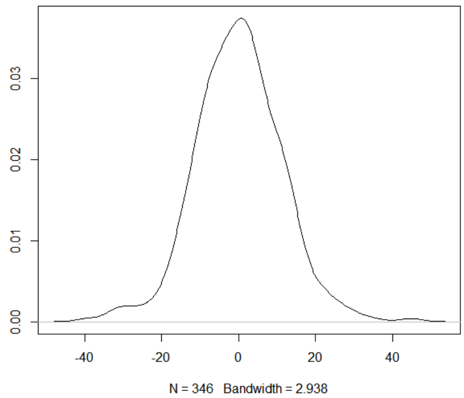
First, we omit control variables one at a time. Results summarized in Table A3 in the Appendix show that the coefficient obtained for *progtax* remains always significant at least at the 0.10 level. We also redid all of our tests by omitting *progtax* in order to verify whether the top tax rate alone would produce any meaningful coefficient, but this was never the case in all of our models. Even when *TOPTR* shows some statistical significance when used as a control variable together with one of our progressivity indicators, it loses it if such indicator is omitted.

We rule out the possibility of a bias due to omitted variables, as the residuals from all of our model specifications are distributed with mean zero and resembling rather closely a Gaussian distribution. As an example, Figure 2 reports the density plots of the residuals obtained from the four regression models presented in Table 4. A Shapiro-Wilk test confirms that the residuals are approximately distributed according to a Normal distribution.

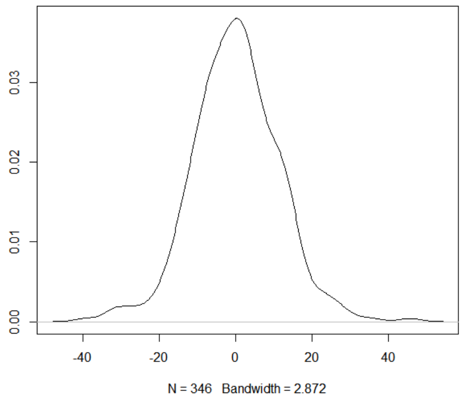
Another set of tests was meant to verify non-stationarity for the time series. To this end, the Phillips-Perron and the Augmented Dickey-Fuller test were used on the variables *progtax* and R&D workforce, rejecting the null hypothesis that the time-series is non-stationary with $p$-value $< 0.01$ for type 2 and 3 non-stationarity. Type-1 non-stationarity (i.e. pure random walk) cannot be rejected, though, for *progtax* (while it is rejected at $p$-value $< 0.05$ for the variable R&D workforce). We therefore checked if switching to first differences of the variables would make the effect disappear, but it is not the case and the coefficients obtained for *progtax* remain statistically significant at the 0.05 level (refer to Table A4 in the Appendix).

R&D workers are endowed with highly specialized human capital which takes several years to accumulate, whether by means of education or learning-by-doing. Therefore, it stands to reason that while exit from R&D jobs into alternative occupations can be readily done by these workers, the opposite probably cannot. To test the hypothesis of asymmetric effects, based on whether tax progressivity increases or decreases, we estimate our fixed-effects specification on a subset of data where we alternatively exclude non-positive or

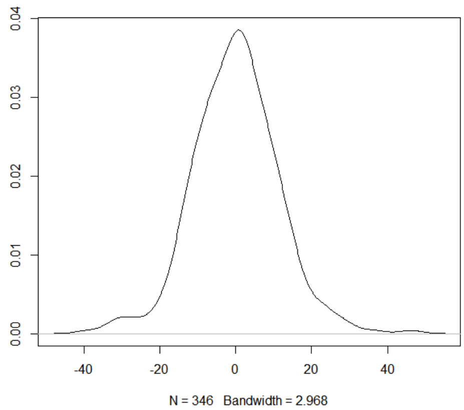
Figure 2: Density plot of residuals



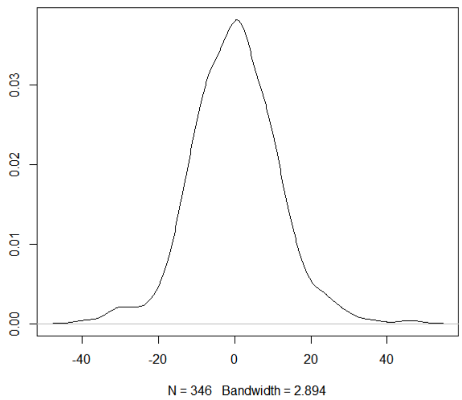

(a) progtax




(b) progtax2




(c) progtax3




(d) progtax4

Table 5: Results (fixed-effects model) using tax rates instead of the tax progressivity indicator. Independent variables are lagged 2 years.

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | (1) | (2) | (3) |
| AVGTRlow | 1.105*** | 1.201*** | |
| | (0.335) | (0.337) | |
| AVGTR | | | 1.146*** |
| | | | (0.410) |
| MTR167 | 0.178 | | 0.116 |
| | (0.220) | | (0.226) |
| TOPTR | | −0.212 | |
| | | (0.192) | |
| revgdp | 0.621 | 1.013 | 0.505 |
| | (0.770) | (0.801) | (0.812) |
| gdp_pc | −0.453*** | −0.483*** | −0.446*** |
| | (0.073) | (0.074) | (0.074) |
| log(population) | 23.953 | 32.645** | 20.152 |
| | (15.995) | (15.495) | (16.424) |
| log(patents) | −2.763 | −2.387 | −3.749* |
| | (2.114) | (2.111) | (2.092) |
| log(GERD) | 23.923*** | 23.775*** | 23.849*** |
| | (3.429) | (3.429) | (3.446) |
| Year | −0.302 | −0.634 | 0.147 |
| | (0.895) | (0.920) | (0.899) |
| Year (squared) | 0.066** | 0.079** | 0.045 |
| | (0.034) | (0.035) | (0.034) |
| Observations | 346 | 346 | 346 |
| $R^2$ | 0.615 | 0.616 | 0.612 |
| Adjusted $R^2$ | 0.579 | 0.579 | 0.575 |
| F Statistic (df = 9; 315) | 55.984*** | 56.150*** | 55.126*** |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

non-negative changes in *progtax*. Table 6 reports results with non-lagged independent variable, while Table 7 employs 2-year lags for comparability with Table 4.

We see that the coefficient for the non-negative changes is indeed larger and has higher statistical significance compared to the main model specification. Moreover, coefficients for the non-positive changes are smaller and lose all statistical significance, and in the model with lags (see column (3) in Table A4) it even reverts sign. We conclude that the effects measured in previous models mostly capture exit from the R&D workers associated with a rise in tax progressivity. We can only assume that, having a longer time series available, we might detect that entry into R&D work also reacts with statistical significance to decreases in tax progressivity (as sort of a long-term behavioural reaction), but unfortunately our data is constrained to a range of time which hardly allows for such long-term analysis.

Table 6: Results (fixed-effects model) from the main model specification (1), and from a reduced dataset only retaining observations where the change in *progtax* is non-negative (2) or non-positive (3).

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | (1) | (2) | (3) |
| progtax | $-46.759^{*}$ | $-90.435^{***}$ | $-37.540$ |
| | (25.621) | (28.414) | (31.329) |
| TOPTR | 0.166 | 0.550 | $-0.022$ |
| | (0.333) | (0.395) | (0.379) |
| revgdp | $-0.012$ | $-1.890$ | 1.042 |
| | (1.175) | (2.175) | (1.310) |
| gdp_pc | $-0.321^{*}$ | $-0.224$ | $-0.487^{*}$ |
| | (0.165) | (0.193) | (0.277) |
| log(population) | 53.105 | 12.176 | 13.410 |
| | (54.248) | (56.815) | (65.462) |
| log(patents) | $-9.476^{**}$ | $-6.350$ | $-15.727^{**}$ |
| | (3.838) | (4.994) | (7.642) |
| log(GERD) | $47.499^{***}$ | $57.753^{***}$ | $53.820^{***}$ |
| | (7.769) | (6.134) | (10.668) |
| Observations | 366 | 169 | 196 |
| $R^2$ | 0.581 | 0.672 | 0.556 |
| Adjusted $R^2$ | 0.545 | 0.604 | 0.482 |

*Note: HC1 robust standard errors in parenthesis.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

A potential issue is endogeneity in the form of reverse causality. It stands to reason that larger R&D investments, which would also imply a larger R&D workforce, can over time produce more innovations and as a consequence, increase the GDP of a country. Increased tax progressivity could then come as a byproduct of Wagner's Law, which predicts that richer countries on average have higher public expenditures due to services (like healthcare) that might be in higher demand and be more efficiently supplied by the public sector (e.g. because of their public good nature). If the latter is true, then the correlation we found between R&D employment and tax progressivity would have inverted causality direction compared to our interpretation of previous models' results and would

Table 7: Results (fixed-effects model using 2-year lags) from the main model specification (1), and from a reduced dataset only retaining observations where the change in *progtax* is non-negative (2) or non-positive (3).

| | *Dependent variable:* | | |
|---|---|---|---|
| | R&D workforce | | |
| | (1) | (2) | (3) |
| progtax | $-34.705^{*}$ | $-139.669^{**}$ | 25.927 |
| | (25.682) | (54.427) | (37.841) |
| TOPTR | $-0.120$ | $-1.064^{*}$ | 0.367 |
| | (0.362) | (0.593) | (0.423) |
| revgdp | 1.304 | $-4.701$ | 1.376 |
| | (1.608) | (3.415) | (2.236) |
| gdp_pc | $-0.498^{**}$ | $-0.057$ | $-1.160^{***}$ |
| | (0.201) | (0.255) | (0.336) |
| log(population) | 36.328 | $189.910^{**}$ | 12.083 |
| | (37.597) | (68.513) | (36.752) |
| log(patents) | $-2.484$ | $-1.605$ | $-9.010$ |
| | (3.505) | (9.284) | (6.421) |
| log(GERD) | $24.358^{***}$ | $35.029^{***}$ | $42.523^{***}$ |
| | (5.849) | (11.695) | (8.816) |
| Observations | 346 | 38 | 76 |
| $R^2$ | 0.610 | 0.877 | 0.656 |
| Adjusted $R^2$ | 0.573 | 0.715 | 0.494 |

*Note: HC1 robust standard errors in parenthesis.*
*All independent variables are 2-year lags.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

just capture a generally higher level of taxation, used to finance such increased public spending. Another reason for reverse causality might be that larger R&D investment causes more inequality over time via skill-biased technological change, which would then increase demand for redistribution policies.

We rule out these possibilities on several grounds. First, our main model specification employs two-year lags of the independent variables, thus mitigating reverse causality biases thanks to the principle according to which the future cannot affect the past. Second, we see that none of our indexes for tax progressivity correlate with GDP per capita, which goes against both hypotheses of reverse causality mentioned above. By the same token, *R&D Workforce* does not appear to predict larger production of patents (e.g. see the correlation matrix in Table A2), which makes sense as productivity in innovation also stems from capital investments, the accumulation of human capital and the nature of the national innovation system. To put it in other words: a larger R&D workforce may produce a larger absorptive capacity (in the meaning proposed in Cohen and Levinthal 1990) rather than more new-to-the-world innovation which is what patent counts proxy for. Third, the kind of reverse causality based on Wagner's Law would also feature a positive correlation between tax rates on high incomes and the R&D workforce which, as stated already, our results never detect. The reverse causality based on skill-biased technical change would require that increases in tax progressivity are introduced after increases in either investment in R&D (the *GERD* variable in our data) and/or in innovation output (which we proxy with *patents*). Results shown in Table 8 demonstrate that this is not the case and, if anything, patent counts positively correlate with tax progressivity, thus going in the opposite direction compared to our main result of a negative relationship between tax progressivity and R&D employment. We thus conclude that reverse causality is not affecting our main results.

# 5 Conclusions

The main result stemming from this paper is that countries where personal tax progressivity is larger, also have a smaller share of their workforce involved in R&D activities. Because we do not detect any meaningful negative relation between higher tax rates and the resident R&D workforce size, we conclude that most likely there is some mechanism at play related to how workers evaluate entry into, and exit out of, the R&D job market. Whether the main driver is some form of asymmetric information, symmetric uncertainty coupled with credit constraints *à la* Terviö (2009) or some other specific theoretical setting, is a matter that future research will need to clarify. Our empirical results only support a theoretical framework based on asymmetric information.

Our results also suggest no meaningful relationship between marginal tax rates on high incomes and the size of R&D employment in European countries. This needs to be compared to Akcigit et al. (2018) where instead, a large and highly significant coefficient was found for U.S. states when using a count of resident inventors as dependent variable. We have only speculative explanations to offer here, which will require further research to be fully clarified. The first reason for the differing results might be that European countries impose more barriers to moving workers, in the form of heterogeneous institutions and different languages, compared to U.S. states. To the extent that the behavioural reaction

Table 8: Testing reverse causality: Results from a fixed-effects model using 2-year lags, where the dependent variable is a measure of tax progressivity.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | progtax | progtax2 | progtax3 | progtax4 |
| | (1) | (2) | (3) | (4) |
| gdp_pc | 0.0003 | 0.0001 | 0.00001 | 0.0001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| log(patents) | 0.030* | 0.022 | 0.006 | 0.016 |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| log(population) | −0.248** | −0.241** | −0.044 | −0.212* |
| | (0.111) | (0.111) | (0.111) | (0.111) |
| revgdp | −0.009** | −0.004 | −0.008** | −0.007* |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Year | −0.004 | −0.008* | 0.001 | 0.001 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Year (squared) | 0.0003* | 0.001*** | −0.00003 | 0.00002 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) |

*Note: HC1 robust standard errors in parenthesis.*
*All independent variables are 2-year lags.*
*p<0.1; **p<0.05; ***p<0.01

to high marginal tax rates happens in the form of a relocation of the inventor, then such propensity to move might be smaller in Europe compared to the U.S.. Indeed previous studies identified a generally low mobility of workers across the European Union (e.g. Barslund, Busse, and Schwarzwälder 2015), and the same might apply to the subset of workers studied here. A second reason might be due to the choice of the dependent variable. As already stated, innovators defined as those people who applied for at least one patent are a selected crowd that excludes not only the unsuccessful innovators who tried and failed to obtain a patent right, but also those whose innovations cannot be patented at all, either because of the very nature of the innovation (e.g. some software and product design), or because the company they work for favours secrecy over intellectual property. It might be then that these innovators are more mobile geographically compared to the rest of R&D workers, or they have more/better alternative options outside of R&D work (e.g. as entrepreneurs or as academic researchers).

The findings presented herein also partly contrast the ones in Lehmann et al. (2016) where the authors studied the relationship between tax progressivity and unemployment rates for the general workforce, finding that lower average tax rates and higher tax progressivity are both associated with smaller unemployment rates. Our results suggest that, specifically for R&D workers, the relationship might have inverted sign. A likely explanation of the difference can be found in R&D employees rarely falling in the very first income decile(s) which are the ones producing the higher labour supply elasticities driving the results in Lehmann et al. (2016). As we pointed out already, though, the choice of entering R&D functions is best captured by a model where the main alternative option is non-R&D employment, not unemployment. Thus our results are only partly comparable to Lehmann et al. (2016).

Taken together our results bring important policy implications. To the extent that taxation produces (as a by-product of collecting tax revenues to finance public expenditures) a social cost in the form of reduced commitment to R&D work, the results presented herein claim that it is not the level but rather the shape of the tax schedule which may cause such cost. While we believe that under significant international workers' mobility, high tax rates may bring a reduction in highly specialized workforce available in a country because of relocation (as demonstrated many times in the empirical literature cited in previous sections), our results warn about a different mechanism that could, as well, reduce the R&D workforce in absence of cross-border mobility.

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# APPENDIX

Table A1: Descriptive statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| R&D workforce | 366 | 117.779 | 49.613 | 43.180 | 76.243 | 152.960 | 226.420 |
| progtax | 366 | 2.665 | 1.241 | 0.909 | 1.848 | 3.342 | 8.400 |
| TOPTR | 366 | 43.407 | 11.326 | 15.000 | 40.000 | 52.000 | 62.300 |
| AVGTR | 366 | 18.433 | 6.518 | 4.930 | 14.105 | 21.807 | 38.580 |
| AVGTRcouple | 366 | 14.739 | 7.053 | 2.030 | 9.978 | 19.452 | 36.800 |
| AVGTRlow | 366 | 8.456 | 8.477 | −4.850 | 2.155 | 14.785 | 35.400 |
| MTR167 | 366 | 44.367 | 10.545 | 21.280 | 37.000 | 51.500 | 70.960 |
| revgdp | 366 | 12.566 | 5.474 | 4.300 | 8.400 | 15.075 | 33.200 |
| gdp_pc | 366 | 118.562 | 71.473 | 19.400 | 60.025 | 153.150 | 336.100 |
| population | 366 | 18,520.420 | 23,390.640 | 289.521 | 3,422.177 | 16,792.060 | 82,657.000 |
| GERD | 366 | 9,818.995 | 16,699.950 | 37.030 | 727.468 | 10,494.260 | 99,553.620 |
| patents | 366 | 2,395.048 | 4,951.050 | 2.660 | 93.947 | 1,862.925 | 24,396.570 |
| progtax2 | 366 | 0.794 | 0.200 | 0.225 | 0.674 | 0.951 | 1.109 |
| progtax3 | 366 | 0.571 | 0.155 | 0.156 | 0.511 | 0.674 | 0.878 |
| progtax4 | 366 | 0.658 | 0.160 | 0.187 | 0.576 | 0.769 | 0.933 |

Table A2: Correlation matrix

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) R&D workforce | 1 | -0.132 | 0.528 | 0.438 | 0.420 | 0.408 | 0.510 | 0.668 | 0.741 | -0.122 | 0.188 | 0.148 | -0.146 | -0.016 | -0.095 |
| (2) progtax | -0.132 | 1 | 0.350 | -0.708 | -0.624 | -0.486 | 0.076 | -0.244 | -0.089 | 0.239 | 0.045 | 0.012 | 0.637 | 0.831 | 0.746 |
| (3) TOPTR | 0.528 | 0.350 | 1 | 0.291 | 0.280 | 0.228 | 0.792 | 0.610 | 0.456 | 0.211 | 0.297 | 0.251 | 0.213 | 0.405 | 0.271 |
| (4)AVGTR | 0.438 | -0.708 | 0.291 | 1 | 0.955 | 0.810 | 0.435 | 0.735 | 0.309 | -0.168 | 0.040 | 0.060 | -0.643 | -0.638 | -0.690 |
| (5) AVGTRcouple | 0.420 | -0.624 | 0.280 | 0.955 | 1 | 0.930 | 0.383 | 0.773 | 0.279 | -0.271 | -0.086 | -0.088 | -0.771 | -0.635 | -0.764 |
| (6) AVGTRlow | 0.408 | -0.486 | 0.228 | 0.810 | 0.930 | 1 | 0.298 | 0.740 | 0.205 | -0.381 | -0.224 | -0.250 | -0.866 | -0.570 | -0.751 |
| (7) MTR167 | 0.510 | 0.076 | 0.792 | 0.435 | 0.383 | 0.298 | 1 | 0.619 | 0.480 | -0.051 | 0.111 | 0.113 | 0.096 | 0.372 | 0.248 |
| (8) revgdp | 0.668 | -0.244 | 0.610 | 0.735 | 0.773 | 0.740 | 0.619 | 1 | 0.641 | -0.107 | 0.073 | 0.036 | -0.385 | -0.168 | -0.317 |
| (9) gdp_pc | 0.741 | -0.089 | 0.456 | 0.309 | 0.279 | 0.205 | 0.480 | 0.641 | 1 | -0.098 | 0.111 | 0.098 | 0.029 | 0.105 | 0.043 |
| (10) population | -0.122 | 0.239 | 0.211 | -0.168 | -0.271 | -0.381 | -0.051 | -0.107 | -0.098 | 1 | 0.832 | 0.794 | 0.450 | 0.216 | 0.317 |
| (11) GERD | 0.188 | 0.045 | 0.297 | 0.040 | -0.086 | -0.224 | 0.111 | 0.073 | 0.111 | 0.832 | 1 | 0.945 | 0.309 | 0.088 | 0.184 |
| (12) patents | 0.148 | 0.012 | 0.251 | 0.060 | -0.088 | -0.250 | 0.113 | 0.036 | 0.098 | 0.794 | 0.945 | 1 | 0.312 | 0.059 | 0.174 |
| (13) progtax2 | -0.146 | 0.637 | 0.213 | -0.643 | -0.771 | -0.866 | 0.096 | -0.385 | 0.029 | 0.450 | 0.309 | 0.312 | 1 | 0.788 | 0.913 |
| (14) progtax3 | -0.016 | 0.831 | 0.405 | -0.638 | -0.635 | -0.570 | 0.372 | -0.168 | 0.105 | 0.216 | 0.088 | 0.059 | 0.788 | 1 | 0.950 |
| (15) progtax4 | -0.095 | 0.746 | 0.271 | -0.690 | -0.764 | -0.751 | 0.248 | -0.317 | 0.043 | 0.317 | 0.184 | 0.174 | 0.913 | 0.950 | 1 |

Table A3: Results from the main fixed effects model, with stepwise omission of a control variable.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | R&D workforce | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| progtax | $-34.351^{*}$ | $-42.416^{***}$ | $-39.941^{**}$ | $-37.838^{**}$ | $-51.289^{**}$ | $-36.718^{*}$ |
| | (19.343) | (15.115) | (18.873) | (18.417) | (20.234) | (19.404) |
| revgdp | 1.116 | | 1.032 | 1.228 | 0.607 | 1.972 |
| | (1.282) | | (1.488) | (1.647) | (1.427) | (1.674) |
| TOPTR | | −0.005 | 0.217 | 0.002 | −0.112 | −0.178 |
| | | (0.228) | (0.335) | (0.348) | (0.335) | (0.321) |
| gdp_pc | $-0.486^{**}$ | $-0.462^{**}$ | | $-0.452^{**}$ | $-0.395^{**}$ | −0.245 |
| | (0.193) | (0.186) | | (0.212) | (0.177) | (0.167) |
| log(population) | 33.656 | 30.747 | 9.216 | | 29.775 | 9.584 |
| | (39.229) | (35.571) | (56.214) | | (39.164) | (44.948) |
| log(patents) | −2.579 | −2.812 | −2.924 | −4.225 | | 4.517 |
| | (3.001) | (2.927) | (2.992) | (2.923) | | (2.934) |
| log(GERD) | $24.442^{***}$ | $24.312^{***}$ | $18.069^{**}$ | $23.189^{**}$ | $25.350^{***}$ | |
| | (8.606) | (8.580) | (8.685) | (8.953) | (8.068) | |
| Year | −0.508 | −0.659 | 0.488 | 0.155 | −1.477 | 1.922 |
| | (1.659) | (1.562) | (1.729) | (1.545) | (1.560) | (1.313) |
| Year (squared) | 0.070 | 0.078 | 0.044 | 0.054 | $0.101^{**}$ | 0.027 |
| | (0.054) | (0.049) | (0.056) | (0.044) | (0.045) | (0.053) |
| Observations | 346 | 370 | 346 | 346 | 375 | 354 |
| $R^2$ | 0.610 | 0.606 | 0.555 | 0.603 | 0.603 | 0.515 |
| Adjusted $R^2$ | 0.574 | 0.570 | 0.514 | 0.567 | 0.569 | 0.470 |

*Note: HC1 robust standard errors in parenthesis.*
*All independent variables are 2-year lags.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Table A4: First-difference model

| | *Dependent variable:* |
|---|---|
| | R&D workforce |
| progtax | $-17.025^{**}$ |
| | (7.646) |
| TOPTR | $-0.082$ |
| | (0.138) |
| revgdp | $-0.938^{*}$ |
| | (0.522) |
| gdp_pc | $-0.219^{***}$ |
| | (0.052) |
| log(population) | 3.585 |
| | (50.152) |
| log(patents) | $-0.557$ |
| | (0.779) |
| log(GERD) | $30.935^{***}$ |
| | (7.312) |
| Year | $-1.830$ |
| | (1.171) |
| Year (squared) | $0.084^{**}$ |
| | (0.037) |
| Constant | 0.834 |
| | (1.113) |
| Observations | 343 |
| $R^2$ | 0.173 |
| Adjusted $R^2$ | 0.150 |

*Note: HC1 robust standard errors in parenthesis.*
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01