TAXATION AND THE DOMESTIC MOBILITY OF INVENTORS IN THE UNITED STATES

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Abstract:

This paper investigates the influence of top marginal tax rates on the location preferences of top-tier inventors. We calculate elasticities for different states and years, assessing how inventors respond to changes in the top marginal tax rate. The paper combines the inventors' patent data with location choice and the citation data cited from the United States and European Patent Offices together. We use adjusted citation data as a proxy for inventors' income levels and apply a location choice model. Our findings reveal a positive and statistically significant correlation between the retention of top marginal tax rates and location preferences across all states, with a country-level elasticity of 1.71. Elasticities vary among states, with the highest value of 1.82 observed in Alaska and the lowest value of 1.58 in California. Notably, more innovative states tend to exhibit lower elasticities. Furthermore, our analysis demonstrates that different income groups among inventors respond differently to changes in tax rates, with the top one percent of inventors showing greater sensitivity to fluctuations in the top marginal tax rate.

Introduction:

In the United States, personal income taxes vary significantly from state to state, resulting in varying high top marginal tax rates (MTRs). For instance, California, Oregon, and New York have top MTRs of 14.67 percent, 9.9 percent, and 11.7 percent, respectively. In contrast, states like Washington, Texas, Florida, and six others impose zero income tax. While the average tax rate (ATR) is typically what a rational and fully informed taxpayer should consider when deciding on a location, this paper specifically focuses on the marginal tax rate as an instrument for assessing the ATR, given the unique characteristics of top-tier inventors. Given the substantial disparity in tax rates among inventors, one might question whether these tax rates influence their choice of location. Figure 1 illustrates the significant variations in top marginal income tax rates across different geographical regions. Notably, this variation is not only evident among states but also across different time periods. Empirical examples span from the early 20th century when progressive income tax policies were

introduced, leading to a peak marginal tax rate of 70% in the mid-1930s, to significant changes such as the Economic Recovery Tax Act of 1981 and the Tax Reform Act of 1986, which reduced top marginal tax rates to 50% and 28%, respectively. Figure 2 provides insights into the variation in marginal tax rates among different income groups over the past century. High-income workers experience significantly larger fluctuations, as their top marginal tax rates are both higher and more volatile throughout this period. It is evident that a sharp decline occurred after 1981 in the top marginal tax rate, and this decline persisted until 1988.

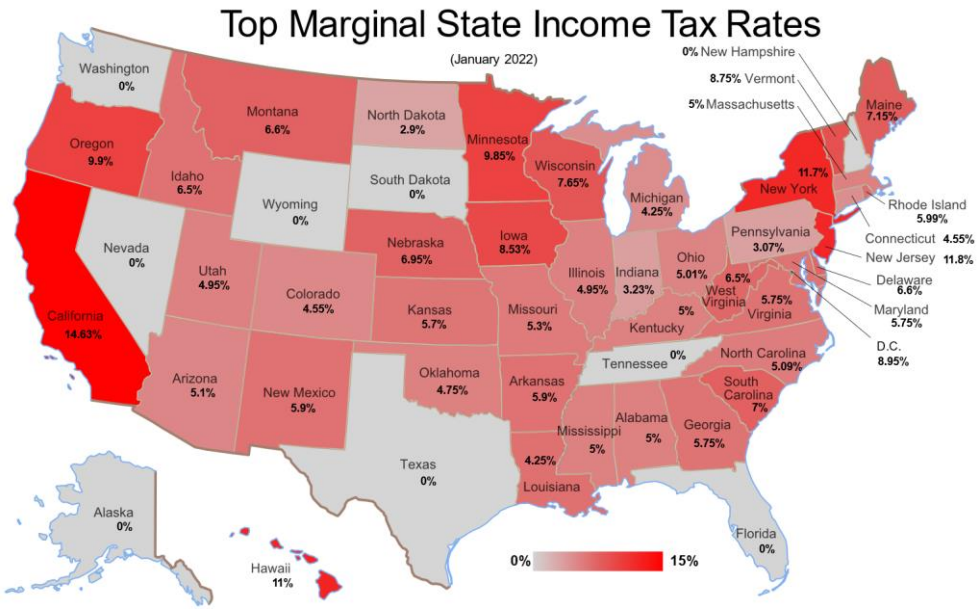


Figure 1. State Top Marginal Income Tax Rate in 2022

(Source: https://taxnews.ey.com/news/2022-0007-2022-state-income-tax-and-supplemental-withholding-rates-preliminary-as-of-january-5-2022)

A significant concern for local governments arises from the potential outflow of elite workers in response to changes in the marginal tax rate. This concern was particularly prominent in 2014 when state taxes and their impact on local positions became a central focus in gubernatorial races. Recently, with the increasing affordability of mobility, paying attention to mobility reactions when designing tax policies has gained greater significance. Many states have engaged in competition to attract firms

by lowering their tax rates.

Furthermore, the rise in top income shares from the 1970s to the 2000s can be attributed to an increase in wage income, as demonstrated by Jesse Bricker et al. (2015), where wage income became a larger contributor to total income than capital income. Top inventors earning in the highest income brackets each year faced mounting pressure due to the upward trajectory of the top marginal income tax rate. It is conceivable that the effect of the top marginal tax rate on inventors, particularly those who make substantial contributions to firms and the economic development of states, may prompt them to react through mobility as a means to avoid the impact of subjective income tax changes.

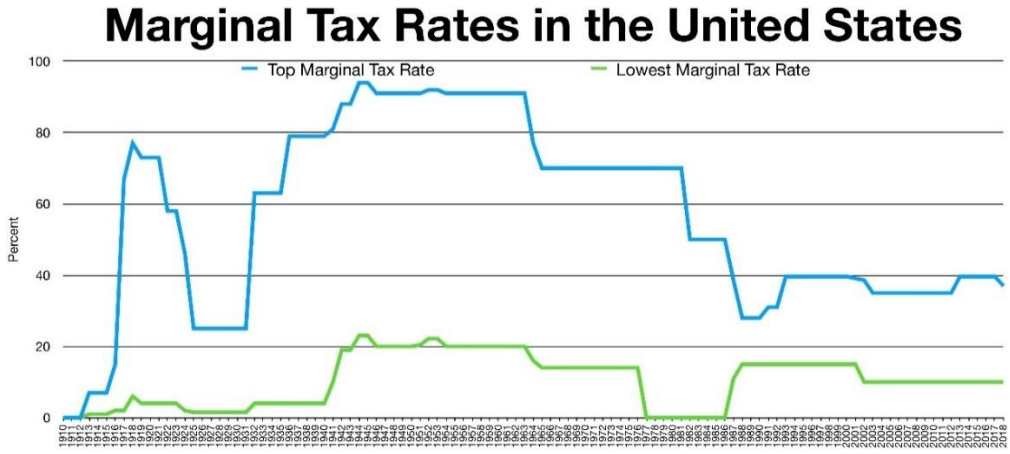


Figure 2. Marginal Tax Rate Change Overtime for High/Low Income Individuals

(Source: Tax Foundation: https://taxfoundation.org/historical-income-tax-rates-brackets/)

Throughout the twentieth century, the United States underwent significant changes in its tax code. However, due to a lack of demographic information, there has been limited insight into how these tax changes influenced innovation at the individual, corporate, or state levels. Few studies have focused on the mobility of inventors in response to tax changes in recent years. For instance, in 2018, Akcigit et al. examined inventors between 1940 and 2000, with a focus on variations in tax rates within

countries over time. Their study, though informative, concentrated on a small geographic sample of eight states, despite demonstrating the high mobility of inventors on average. Similarly, Moretti & Wilson (2017) investigated the impact of state taxes on the migration of prominent scientists across U.S. states. They discovered a substantial elasticity of 1.8 concerning personal taxes among the top 5% of inventors. However, neither study delved deeper into the elasticity of mobility at the state level, which could provide greater insights into the location choices of top inventors. Furthermore, considering that the effects of the top marginal tax rate vary among different income groups, it is essential to conduct a comprehensive comparison of the tax effects on each income group to obtain a more representative understanding of the tax's impact on star inventors.

In this paper, I leverage recent advancements in patent location data availability and enhanced software processing power. Firstly, I identify the highly mobile top 1% of inventors' responses to changes in the top marginal tax rate at the state level, revealing a significant positive correlation between the retention of the top marginal tax rate and location choice. To capture the varying effects of the top marginal tax rate on top inventors, I further categorize inventors based on their citation percentile into different groups. These distinct 'income' groups share enough similarities to be subject to the same state-year level policies and economic effects. The lower percentile group serves as a control group, allowing us to capture the baseline trend for policy variations and economic impacts. Instead of employing a linear model, as done by Moretti & Wilson (2017), I opt for a discrete choice model as the baseline model to assess the sensitivity of top star inventors' location choices in response to changes in the top marginal tax rate. Specifically, I employ a multinomial logit model, which offers greater intuitiveness and relevance. This model can more effectively predict individual selection preferences, offering insights not only into overall elasticity but also into elasticities within different states. This approach provides a more comprehensive understanding of the agglomeration effect among inventors.

The primary dataset for this paper is derived from a panel dataset known as the "Disambiguated Inventor Data," as compiled by Lai et al. (2012). This dataset is centered around inventors who have filed patents with the United States Patent Office (USPTO). It offers the unique capability to track inventors over time and observe various aspects of their innovations, including citations, place of residence, and technological fields. To maintain data consistency and due to observation limitations, I have constrained my analysis to the time period spanning from 1977 to 1999. Furthermore, I have augmented the patent data by merging it with citation data sourced from the National Bureau of Economic Research (NBER). This linkage is facilitated by the use of patent numbers for matching purposes. Lastly, data pertaining to the top marginal tax rates has been obtained from the TMR TAXSIM model, specifically NBER's TAXSIM calculator, covering each state and year of interest.

During the baseline regression analysis, one of the primary challenges lies in the unavailability of micro-level income data for individuals through public websites. To address this limitation, I have adopted a methodology inspired by Akcigit et al. (2016), using adjusted citations as a proxy to estimate the income bracket of inventors. However, it's crucial to acknowledge the tradeoff between the quality and quantity of these citations, given the substantial heterogeneity between the two variables. To assess the quality and quantity of citations, I have employed three different methods. However, the primary approach, referred to as "truncation adjustment citation," follows the framework established by Hall, Jaffe, and Trajtenberg (2001). This method places importance not only on the quantity but also on the quality of an inventor's patents. It takes into account the timing of patents, which adds a practical dimension to the analysis. The other two methods assign different weights to patent quality and quantity. These alternative methods are used as robustness checks for the baseline model, providing a comprehensive assessment of the income proxy's effectiveness and reliability.

Above all, despite the use of different models, the baseline regression results align consistently with those reported by Moretti & Wilson (2017). Specifically, the overall coefficients for the top 1% of inventors are positive and statistically significant. Moreover, these coefficients reveal a noteworthy downward trend for lower income groups, signifying a heightened sensitivity to changes in the marginal tax rate when it comes to location choice among the top 1% of inventors. The robustness of these results is further evidenced by the strong and similar coefficients observed for mean citation and patent count. However, it's important to note that the significance levels for various income groups subject to the top marginal tax rate suggest that a reasonable range for top inventor incomes may extend to 5%-10%. It's worth highlighting that, due to software restrictions, this paper primarily focuses on the top 1% income group.

The second part of this paper involves analyzing the diverse elasticities observed across different states. To accomplish this, I predict the probability of location choices for each state. Subsequently, I calculate the elasticity for each individual state. To arrive at an overall elasticity for the entire country, I compute an average of the state-level elasticities, resulting in a value of 1.71. Interestingly, this value closely mirrors the figure calculated by Moretti and Wilson (2017), who utilized linear models, arriving at a value of 1.8. It's worth noting that the slightly lower elasticity in this study may be attributed to the selection of a shorter and older time period. Furthermore, when states are ordered based on their elasticity, a striking observation emerges: many of the low elasticity states, such as California and New York, are among the most innovative states when considering the total number of patents granted from 1940 to 2000 (as documented by Akcigit et al. (2018)). One possible explanation for the observed low elasticity in tax-location regression is the presence of a substantial agglomeration of top inventors in these states. These agglomerative and spillover effects may overpower the influence of tax-related factors on mobility,

rendering inventors less sensitive to changes in tax rates.

To enhance the robustness of this paper's findings, additional analysis and tests are warranted, particularly to control for the agglomeration effect while introducing other fixed effects into the model. While this study does not initially incorporate fix effects and other control variables, I have included state-yearly personal income per capita as an alternative control variable in the choice model. The aim here is to account for state-year effects. Interestingly, the coefficient associated with this variable is found to be significantly positive. As previously discussed, a higher state personal income per capita can be regarded as an indicator of favorable amenities or externalities that attract top inventors to select a particular location.

In summary, this paper delves into the impact of the top marginal tax rate on inventors' decisions regarding their location across the 51 states in the United States. A discrete choice model, specifically McFadden's Choice Model, was selected for this analysis, and the resulting elasticities for various states were calculated. The findings underscore a robust and positive correlation between the top 1% of inventors and their location choices. The primary contribution of this study lies in its use of a logit model, which serves to bolster the results reported by Moretti & Wilson (2017). Additionally, the computation of elasticities at both the country and state levels provides valuable insights into the dynamics of mobility within each state.

Literature Review:

My paper falls within a niche of studies focusing on the intersection of taxation and location decisions. The issue of migration, often viewed as a cost associated with resource redistribution, has gained prominence in an era of globalization and reduced mobility costs. This shift underscores the importance of considering mobility responses when designing tax policies, as noted by Kleven et al. (2019).

Existing research on migration and taxation in the United States has yielded mixed results. Cohen, Lai, and Steindel (2011) found inconclusive evidence regarding population migration driven by taxation. Similarly, Young and Varner (2011) and Varner and Young (2012) discovered no evidence of tax-induced migration in millionaire tax cases in California and New Jersey. Suarez Serrato and Zidar (2014) focused on corporate taxes, uncovering moderate effects on wages, total employment, and land prices. Giroud and Rauh (2015) examined the impact of business tax on the number and size of enterprises, while Bakija and Slemrod (2004) identified modest effects of state personal income taxes on the number of federal estate tax returns.

Some research has also explored taxation and international mobility. Akcigit, Baslandze, and Stantcheva (2015) conducted a study similar to mine, focusing on scientists and finding elasticity in the number of domestic and foreign inventors concerning personal income tax rates. However, their study operated on a global scale instead of a domestic study. Kleven, Landais, and Saez (2013) centered their research on European soccer players, while Kleven et al. (2014) examined a specific tax change in Denmark and found elasticities ranging from 1.5 to 2.0.

Akcigit et al. (2018) conducted a comprehensive analysis of domestic tax-induced migration in the United States. However, they limited their sample to eight innovative states. The study most closely related to mine is Moretti and Wilson (2017), which explored the effect of state taxes on the migration of star scientists across U.S. states. They discovered that the top 5% of inventors exhibited a high elasticity of 1.8 concerning individual taxes. However, they used a linear model and computed only country-level elasticity. As computational power has advanced, my paper leverages different methods to further test our hypotheses.

Setting, Data, and Strategy:

Historical Patent Data and Inventor Panel Data:

Following the methodology outlined by Akcigit et al. (2016), the primary source of inventor data for this study is the Disambiguated Inventor Data (referred to as DID), compiled by Lai et al. (2012). This panel dataset offers comprehensive descriptive statistics for individual and collaborative variables, shedding light on various networks, including those associated with individuals, organizations, technologies, and regions, with information on countries and states.

The original data is sourced from the U.S. Patent Office (USPTO) and provides unique identifiers for inventors associated with each patent in each year. The USPTO dataset covers a substantial 4.2 million patents granted between 1975 and 2010 and encompasses 3.1 million inventors. This dataset accounts for 18% of direct patent applications and 26% of all patents globally. While the data enables tracking of inventors by location and name each year and allows for the calculation of the total number of patents for each individual, it lacks essential characteristics for patents, such as inventors' patent quality and technology class. To address this limitation, I merge the inventor data with the NBER patent data using the patent number, which provides information on citations received by each patent each year. However, it's essential to note that newly granted patents may exhibit a higher citation bias as citations tend to increase over time. Therefore, to ensure robustness, I restrict my sample to a narrower time range spanning from 1977 to 1999. Within this selected time period, top 1 percent inventors for a given year are identified as those who rank at or above the 99th percentile in terms of the number of adjusted citations they've received over the past ten years. For further insights into the dataset, Table 1 presents a summary of statistics for the merged data.

Table 1: Summary Statistical Results of the Relevant Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Grant_Year	109,264	1,991.598	5.947	1,977	1,987	1,997	1,999
Tax_Rate	109,264	43.963	7.974	28.000	40.790	46.740	75.940
Patent_Count	109,264	23.066	21.369	1	12	28	715
Citation_Count	109,264	253.260	255.562	45	144	285	18,409
Mean_Citation	109,264	16.440	21.071	0.972	7.000	17.684	686.000
GDP	109,264	25,356.320	6,680.829	9,450.431	19,993.230	31,424.440	34,479.790

Certainly, the inclusion of country records for each inventor per year in the DID dataset is a significant advantage. This feature provides the opportunity to track not only the inventors' states of residence but also their home countries over time. Such detailed information holds the potential to offer deeper insights into the elasticity of labor supply, shedding light on the complex dynamics of inventor mobility and the factors influencing their location choices.

A Basic Model of Inventor Migration:

In this part, I follow Akcigit et al. (2016)'s assumption, consider the following very simple model of inventor migration. There are S states in United States (I choose 51 States here because the top marginal tax rate availability), labeled as $s \in \{1, ..., S\}$. The wage of inventor i in state s' at time t is denoted by $w^i_{s't}$. Let $\widetilde{w}^i_{s't}$ denote the corresponding marginal product. The index i indicates the marginal product can depend on several inventor's demographic characteristics, such as skill level, age, and the characteristics of firm or employer. If the domestic labor market is perfectly competitive, each inventor is paid his marginal product, so that $w^i_{s't} = \widetilde{w}^i_{s't}, \forall s', t, i$. Suppose that in state s, an inventor whose location of s^i must pay the tax rate $\tau_{s^i_t}$ on his gross income at time t, which is determined only by the current state tax rate. Apart from the income earned, there is also a net utility benefit denoted $\mu_{s^i_t}$ from locating in states at time t for inventor i. This benefit is personal-dependent and can include: a home bias and other characteristic of the states, or distance to the home states, which capture the individual and state-specific effects. Firstly I assume that there is no significant difference between the international and domestic top star

inventors, only within US factor matters. Actually, this is a good approximation for tax choice if there are many possible origin and destination states and each is relatively small. Hence, to a first order, the probability that inventors locate in state s will depend only on τ_{st} and the relationship should be negative, suggesting a higher tax rate subject to a lower possibility to stay. Thus, total utility from choosing states s at time t for inventor i is given by:

$$U_{st}^{i} = u(w_{st}^{i}(1 - \tau_{s^{i}t}) + \mu_{st}^{i})$$

If to a first order there are no adjustment costs of moving, the decision of where to locate every period is history-independent. Hence, state s will be chosen in period t if and only if:

$$u(w_{st}^{i}(1-\tau_{s^{i}t})+\mu_{st}^{i}) \in argmax_{s'} \left\{ u(w_{s't}^{i}(1 - \tau_{s'^{i}t}) + \mu_{s't}^{i}) \right\}$$

Note that as I discussed before, the specific preferences $\mu_{s}^{i}{}_{t}$ for individuals can significantly determine the location choice, these preferences encompass a range of factors, including agglomeration effects, which can exert a substantial influence on an individual's decision regarding where to reside. In some cases, these location preferences may even completely overshadow the impact of tax rates. Given this complexity, it becomes evident that strong location preferences, which are independent of income considerations, have the potential to dilute the sensitivity of tax rates in influencing location choices. Therefore, it's imperative to incorporate robust controls for these factors in the analysis to disentangle the true effect of tax rates on location choice.

Constructing quality measures for inventors:

As previously mentioned, both the number of citations and the quantity of patents can serve as indicators of an inventor's ability, which, in turn, determine the income level for each inventor (see Hall, Jaffe, and Trajtenberg (2001), Kogan et al. (2012), Moser

et al. (2012), Abrams, Akcigit, and Popadak (2013)). I use three different methods to measure the quality of the patent, showing a trade-off between the patents' quantity and quality. Let p_{ij} be the truncated adjusted number of forwarded citations received by inventor i's patent j. Note that this number is independent of time t, because it counts all the forwarded citations received by the patent in the past and in the future, not only the number of citations received before time t. This truncated method gives a static value for each patent that is not biased by the time variance. Let P_t^i be the set of patents of inventor i by the end of period t. And both patent quality and quantity are considered. Above all, the method $q1_t^i$ can be denoted as:

$$q1_t^i = \sum_{j \in P_t^i} pij \qquad (1)$$

Measure q1 focusing on accumulated citations as a measure of one's influence. Then I define the measure $q2_t^i$, it is basically the current patent count namely:

$$q2_t^i = \left| P_t^i \right| \qquad (2)$$

Measure q2 totally focus on the quantity of the inventors ignoring the quality. Finally, the third measure $q3_t^i$, measure the mean number of citations per patent:

$$q3_t^i = \frac{\sum_{j \in P_t^i} p_{ij}}{\left| P_t^i \right|} \qquad (3)$$

Based on these measures of quality or quantity, we can create a ranking of inventors and, in particular, identify the "most innovative" inventors. I define a superstar at time t as the top 1% of the regional adjust citation distribution at time t. Similarly, I calculated the top 5%, top 10%, and top 25%. Note that the measures for quality ranking are dynamic measures in the sense that they can change over an inventor's lifetime, depending on which quality bracket he falls in in the regional distribution of

quality in any given year. To further measure the tax effect on the different quality groups in order to precise targeting of groups affected by the opponent's top marginal tax rate, I use the notation “top 1-5%” to denote inventors who are in the top 5% excluding the top 1%, and, similarly the top 5-10% and top 10-25% to respectively denote inventors in the top 10% excluding the top 5%, and in the top 25%, excluding the top 10%, respectively.

Making use of the Inventor and Top Tax Rate Data:

I take 3 steps for measuring the counterfactual earnings for individuals in each year.

1. Estimating the counterfactual earnings:

Although we cannot observe the inventors’ income directly, we can still use enough information in the data to poxy the counterfactual income. The primary measure is the patent quality and quantity mentioned in equations (1) to (3). A composite measure of patent quality to date is a dynamic statistic that takes into account an inventor’s past achievements. Thus, it is a measure of inventor ability or earnings potential, and a reflection of the inventor’s “resume” (Akcigit et al. (2016)). Patent quantity and the quality should influence the inventors’ income directly and indirectly. Usually, bonus is applied for the direct compliment of innovation, while indirectly, employers tend to pay a higher wage to elite inventors in order to attract the talented and gain a larger amount of talent human capital (Chesbrough, 2006). However, the positive relation between the patent citations and income is highly skewed to the high-quality inventors. Toivanen and Vaananen (2012) finds a highly cited patents receive a higher premium. Based on all this evidence, it is reasonable to take patent quantity or quality measurements as proximations for the inventors’ counterfactual income.

2. Using the effective top marginal tax rate:

"I employ the effective top marginal tax rate as a tax measure. The actual income tax rate for an individual taxpayer is endogenous, meaning it depends on their income.

Consequently, when conducting a regression to explain income in terms of after-tax prices, caution should be exercised when directly using the actual tax rate as an explanatory variable. However, variations in state tax laws across different states and years are exogenous to individual labor supply and income realization decisions. Therefore, I use top marginal income tax rate that relies solely on state laws (or, to a lesser extent, the year) and is not influenced by individual characteristics, making it a potentially valid instrument. It accurately represents tax rates applicable to top inventors on property income and is not influenced by individual decision-making. Moreover, according to computations by Moretti and Wilson (2017), changes in the top marginal tax rate exhibit a strong correlation with changes in the average tax rate for the top 1% of the income distribution."

For the regression analysis, I calculate tax rates for the maximum state tax by year and state using a TAXSIM model. It's important to note that the top federal tax rate varies across states due to the deductibility of state income taxes on the federal tax. Since some states have a top state-level marginal tax rate of zero, I utilize the total top marginal tax rate, which combines both state and federal top marginal tax rates. This approach allows me to derive the top marginal tax rate for all 51 states in a particular year within the time frame of 1977-1999.

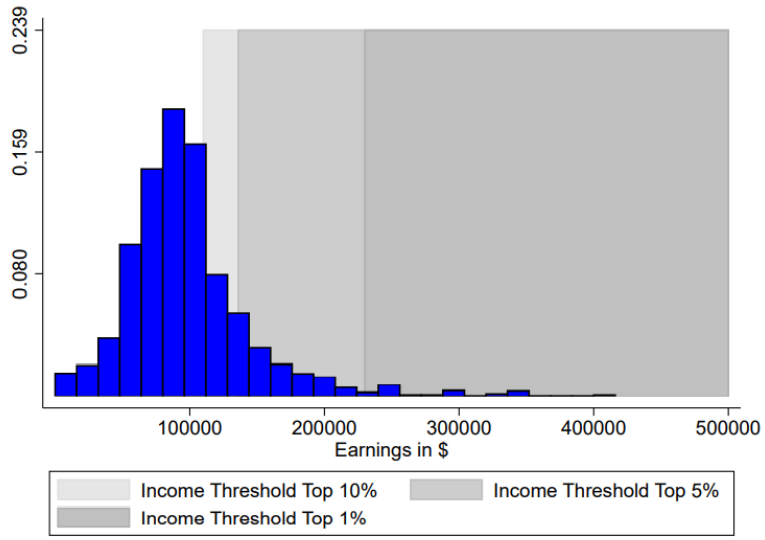
3. Identification using different quality inventors:

The most fundamental identification strategy considers differences in the top marginal tax rate across states and over time. To address the need for detrending, it becomes essential to account for state fixed effects, year fixed effects, and state-specific linear trends. These controls help filter out state-specific long-term trends in innovation, income, and migration. At this early stage of the paper, fixed effects have not yet been incorporated. However, a portion of the fixed time and state effects can be integrated into state-specific linear trends. To address this characteristic, I have incorporated control for personal income per capita for each individual per year. As previously

discussed, there are other factors, such as the business environment or policies aimed at promoting research, which may not only be correlated with location choice but also with the top marginal tax rate (MTR).

In the context of my paper, I have divided income levels into three different groups, with each group being subject to the same state-year level policies and economic effects due to the generally high quality of inventors within each group. However, it's crucial to recognize that only top inventors are directly affected by changes in the top MTR. This comparative approach allows us to filter out variations at the state-year level and explore the differential effects of top marginal tax rate changes on top-tier superstar inventors and those of slightly lower quality. In a way, this measure resembles a "fuzzy regression discontinuity design," where other groups serve as a control group for the top 1% inventors.

Following the strategy of comparing the tax impact on different income groups, the next step is to identify top star inventors who belong to the highest income bracket. This entails distinguishing inventors in the top percentile groups from those in lower percentile groups, considering their declining citation quality levels. Figure 3, based on data from the 2003 National Survey of College Graduates' public-use microdata provided by the NSF (NSF, 2003), reveals interesting insights. It shows that 44% of inventors fall within the top 10% of the U.S. income distribution, 18% are in the top 5%, and 1% are in the top 1% of the U.S. income distribution. It is reasonable to assume that the 1% are most likely to occupy the highest positions in the income distribution, while those in the top 5% to 10% percentiles may also significantly overlap with the top income bracket.



Notes: The data is from the 2003 National Survey of College Graduates public-use microdata from NSF (NSF, 2003). The earnings represented are those of the college graduates with at least one patent and who report being currently employed. The sample size is 3142.

Figure 3. Distribution of Inventor Earnings in the NSF Survey 2003

(Source: Akcigit, Ufuk, Grigsby, John, Nicholas, Tom, & Stantcheva, Stefanie. (2018). *Taxation and Innovation in the 20th Century*. America Economic Association.)

Location Choice Model Estimation:

In this section, I will place the basic results for my baseline model estimation from the multinomial location model.

Specification and estimate:

Utility function and controls:

Because top MTR is directly determined by the state and year, I adopt a McFadden's Choice model which is belonging to multinomial discrete-choice model uses conditional logit. Recall the utility function defined in the last section, now, to adjust to the imperial analysis, I use the log form for the utility, which can analyze the wage and top MTR separately. Suppose that the value to inventor i of living (and inventing) in state s in year t is:

$$U_{ist} = \alpha ln(1-topMTR^{i}_{st}) + \beta_s ln(\omega_{ist}) + \gamma x_{st} + \eta_s x_{it} + \delta_s x_{ist} + v_{ist}$$

If the error term v_{ist} has a type I extreme value distribution, this model can be estimated as a multinomial logit. For this paper, the McFadden logit model (Alternative-Specific Conditional Logit) has specific demands on how your data is structured and there are two types variables in general, variables that are case-specific or alternative-specific. Alternative-specific variables variate based on different choices (states), while the case variables are variables that contain personal information. In my model, for example, α is a coefficient related to alternative specific control, which is the retention of $topMTR^i_{st}$: top marginal income tax rate that would apply to inventor i in state s at time t. Similarly, state personal income per capita (PI) can be seen as an alternative choice variable as it varies with the states, and variables like PI are included in x_{st}. By contrast, income w_{ist} is treated as a case specific variable which is mainly individual related, while x_{ist}, x_{it} are a set of other case (individual) specific detailed controls. v_{ist} is an inventor-specific idiosyncratic value of being in state s at time t. If v_{ist} is i.i.d with Type 1 extreme value, then the probability that an inventor locates in state s, denoted P_{ist}, takes the multinomial for:

$$P^i_{st} = \frac{exp(\alpha ln(1 - topMTR^i_{st}) + \beta_s ln(\omega_{ist}) + \gamma x_{st} + \eta_s x_{it} + \delta_s x_{ist})}{\sum_{s'} exp(\alpha ln(1 - topMTR^i_{s't}) + \beta_{s'} ln(\omega_{is't}) + \gamma x_{s't} + \eta_{s'} x_{it} + \delta_{s'} x_{is't})}$$

Since I want to exploit state-by-year variation in the top marginal tax rate, to allow for heterogeneous effects of the top tax rate for different qualities of inventors, I run the regression on top marginal retention rate for groups with different quality rankings. The baseline regression results are shown in Table 2. The controls are described as above, where Top MTR and PI are alternative specific variables while adjust citation is case variables representing the proxy for inventors' income level.

Column 1 of Table 2 presents the specification for top 1% inventors, while the

subsequent columns represent inventors from various income percentiles: top 1% to 5%, top 5% to 10%, and top 10% to 25%, respectively. The table displays the coefficient results obtained from the application of McFadden's Choice Model.

In this analysis, the reference location for choices is defined as "California" (CA). In this context, the coefficients associated with log citations can be interpreted as reflecting the relative change in the probability of choosing CA when citations increase. An interesting observation emerges: regardless of the income group, most inventors exhibit a higher likelihood of selecting CA when there is an increase in citations. This is evident from the negative coefficients observed for most states, with the effect being more significant for top star inventors. Similarly, the coefficients related to retention tax are significantly positive for both top 1% inventors and those in the 1% - 5% income bracket. This indicates that these groups are notably sensitive to changes in the top tax rate. It's important to note that other groups, such as inventors in the 5% - 10% and 10% - 25% income brackets, can be considered as a control group exposed to fewer changes in the top marginal tax rate compared to the first two groups.

Fitness and Robustness:

Prediction versus Frequency: Since the McFadden’s Choice Model is not a typical multi-nominal logit model that other related topics choose to use. In order to show fitness, I further test how closely do average predicted probabilities match the sample. In essence, my goal is to assess whether the sample data can provide accurate predictions for the location choices of star inventors. Table 3 presents a summary of the comparison between the predicted probabilities of choosing each state and the actual frequency of inventors locating in each state. Upon examining the table, it becomes evident that the predicted average probabilities for choosing each state closely align with the observed sample frequencies. This alignment indicates a strong fit of the model to the data, suggesting that the model provides a good representation

of the actual location choices made by inventors. Moreover, the robustness of this model's fit is crucial as it will enable more convincing predictions of elasticities in the subsequent chapters, enhancing our ability to gain valuable insights into the factors influencing inventors' mobility choices.

Patent quality versus quantity measures: While the McFadden's Choice Model serves as an excellent choice for this paper, it is imperative to subject the taxation effect on superstar inventors to a rigorous battery of robustness checks to validate the benchmark results. In this section, I place particular emphasis on our measure of inventor income and the corresponding calculation of inventor ranking, Specifically, I delve into how the results may vary when different measures of 'income' are considered. As previously discussed, there are alternative measures, denoted as q2 and q3, which assign varying weights to patent quality and quantity, respectively. Table 4 shows the correlation between each two measures, the adjust citation q1 is not that highly correlated with both patent count q2 and citation mean q3. Despite the fact that the correlation coefficient for q2 and q3 is closer to 1, it's essential to note that they exhibit a negative correlation. This negates the possibility of providing conclusive regression results for tax rates, given that mean citation equals adjusted citation divided by patent count. In essence, the three measures—mean citation, q2, and q3—are not highly correlated in terms of coefficients, which allows us to employ them as robustness checks.

Table 5 summarize the results for robustness check using alternative quality measures q2 and q3. As we can see, the results are not artificially driven by observing people with more patents more frequently. Moreover, using simple patent counts, the coefficient on the top retention rate becomes much smaller but significant for top 1% inventors, and even smaller by using citation mean though still significant. The

TABLE 5: ROBUSTNESS CHECKS

	Alternative quality Measures		
	q1	q2	q3
Log Retention Rate × Top 1	1.818297*** (0.340602)	1.3095992*** (0.2848729)	1.0306661*** (0.2946629)
Log Retention Rate × Top 1-5	1.2077958*** (0.3630592)	1.9739732*** (0.2861770)	1.0634615*** (0.2880433)
Log Retention Rate × Top 5-10	-0.3714529 (0.3974369)	1.1168658*** (0.2882959)	0.3583442 (0.2879938)
Log Retention Rate × Top 10-25	0.0593936 (0.3229927)	-0.3577264 (0.2769039)	-0.253694 (0.276591)
Observations	109264	109264	109264

Notes: McFadden's Choice Model ——Multinomial logit regressions. All regressions contain the same covariates as Table 2. Only coefficients on Retention top MTR are displaced. Column 1 uses the lifetime measure of inventor ranking ("has ever been or will ever be in the top 1%," etc..). The next three columns use three alternative quality measures to rank inventors into the top 1%, top 1-5%, etc. * p < 0.1, ** p < 0.05, *** p < 0.01

significant and downward trend further indicates the adjust citation q1 is a better measure measurement for top 1% inventors. Interestingly, when employing patent count (q2) as a measure, the coefficient on the tax rate for the Top 1-5 and Top 5-10 inventors is higher and more significant than when using adjusted citation (q1). This suggests that even investors in the top 5% to 10% income bracket may be subject to a top marginal tax rate, which aligns with the findings of Moretti & Wilson (2017) who used patent count as a measure for ranking inventors. However, it's worth noting that while they demonstrate the robustness of inventors at the 10% level using patent count, the consideration of whether the 10% level should be added as a threshold for top inventors warrants further discussion. This is because both the q1 and q3 measures do not yield significant results.

Computing Elasticities:

In this section, owing to the predictive advantages of the logit model, I computed the elasticities for each state, a dimension that has not been previously discussed by

Moretti & Wilson (2017). In order to go from the coefficients on the retention rate to elasticities, I follow the computations in Kleven, Landais, and Saez (2013), the equations are briefly introduced here. In the multinomial model, the elasticity of the probability of inventor i of locating in state s at time t to the net of tax rate $(1-\tau_{st}^{i})$, denoted by ε_{st}^{i}, is:

$$\varepsilon_{st}^{i}=\frac{dlnP_{st}^{i}}{dln(1-\tau_{st}^{i})}=\alpha(1-P_{st}^{i})$$

where α is the effect, defined above, which is the same as the coefficients on retention tax rate for top 1 inventors. Similarly, the state-level elasticity is calculated by:

$$\varepsilon^{s}=\frac{dln(\sum_{i\in Is}P_{st}^{i})}{dln(1-\tau_{st})}=\frac{\alpha\sum_{i\in Is}P_{st}^{i}(1-P_{st}^{i})}{\sum_{i\in Is}P_{st}^{i}}$$

Where ε^{s}represent the elasticity for each state. Finally, average country elasticities, ε^{c}, are defined as the weighted average elasticities across all states:

$$\varepsilon^{c}=\frac{dln(\sum_{s}\sum_{i\in Is}P_{st}^{i})}{dln(1-\tau_{st})}=\frac{\alpha\sum_{s}\sum_{i\in Is}P_{st}^{i}(1-P_{st}^{i})}{\sum_{s}\sum_{i\in Is}P_{st}^{i}}$$

Based on the first two equations, we can initially compute the elasticities of top 1% superstar inventors on a state-by-state basis. To simplify the presentation of results, let's focus on the estimates obtained using the top 1% of inventors. In Table 6, the first column displays the elasticity, while the second column presents the top 1999 MTR for each state. The last column calculates the percentage change in the number of inventors if there were a 10-percentage point reduction in the top tax rate from its actual level in each state in 1999.

The table is ordered based on the increasing level of state elasticities. From the table, we observe that Texas exhibits the lowest percentage change in inventors in 1999, with a figure of 11.12%, while Rhode Island shows the highest percentage change, recording a value of 15.23%. It's important to note that these percentage changes are contingent upon the respective top marginal tax rates in 1999.

However, the most informative results emerge from the state elasticities themselves. Notably, states such as California and New York, which rank among the eight most innovative states in the last century in terms of total patent count (Akcigit et al. (2018)), consistently rank high in this table. This suggests that these states exhibit a lower level of elasticities, indicating a lower sensitivity of inventors to tax rate changes. (The eight states are: California, Maryland, Massachusetts, Minnesota, New Jersey, New York, Ohio, and Wisconsin.)

At first glance, it may appear contradictory that the eight most innovative states exhibit lower elasticity. However, this result is not in conflict with our estimations. One crucial assumption to consider is that for each state, if there is a high elasticity among these highly innovative states, the mobility effects of inventors may dominate the agglomeration effect. Conversely, if the elasticity is low, the agglomeration effect of top inventors may outweigh the mobility effects, suggesting a potentially higher concentration of top talented inventors.

Taxation serves as a mechanism for wealth redistribution, and variations in taxes may be strongly correlated with differences in the availability of public goods and services. While top inventors may experience greater fluctuations in tax rates, they might benefit from better public services and environmentally friendly working conditions in these innovative states. Paradoxically, this could make them more inclined to remain in these states, resulting in a lower elasticity. This assumption is further supported by the sample frequencies calculated in Table 3, which show significantly

higher frequencies for these eight innovative states, indicating a strong preference for choosing to reside there.

When calculating the total elasticity, I computed it as the weighted average of the elasticities for all 51 states, resulting in a value of 1.71. Although our method differs somewhat, the result is relatively close to the figure of 1.8 reported by Moretti & Wilson (2017). It's worth considering that their study covered a longer and more recent time period, which may have contributed to a higher overall mobility for top inventors. This could be attributed to the effects of globalization and the decreasing costs of mobility, as discussed in Wouden (2021).

Conclusion:

In summary, this paper initially employs an Alternative-Specific Conditional Logit model to demonstrate the high mobility of the top 1% of inventors in response to changes in the top marginal tax rate (MTR). This tax effect remains robust even when considering the top 5% of inventors using different ranking measures. Subsequently, the paper calculates and compares the elasticities for each state, shedding light on the potential agglomeration effect in innovative states. Furthermore, the paper calculates the overall elasticity for the entire country, resulting in a value of 1.71. This figure indicates a high level of mobility among the top 1% of US inventors in response to taxation effects.

Looking ahead, as this analysis continues, we plan to introduce additional controls such as a home dummy variable and further investigate the agglomeration effect, as suggested by our previous findings. Additionally, the availability of a dataset containing state and country information offers opportunities for future exploration. Subsequent research could delve into differences between domestic and international inventors, variations in elasticities between state-born and out-of-state-born inventors, and potentially controlling for other tax rates. These endeavors promise to provide a

deeper understanding of the dynamics of location choice among inventors.

Tables:

TABLE 2: EFFECT OF THE TOP RETENTION RATE ON INNOVATORS' MOBILITY

	Log Retention Rate × Top 1	Log Retention Rate × Top 1-5	Log Retention Rate × Top 5-10	Log Retention Rate × Top 10-25
Retention MTR	1.818297***	1.2077958***	-0.3714529	0.0593936
	(0.340602)	(0.3630592)	(0.3974369)	(0.3229927)
PI	1.597657***	1.2289369***	0.73961971***	0.2021334*
	(0.085607)	(0.0929490)	(0.1043538)	(0.0895750)
logcitation:AK	0.169820	0.6084173	0.6661562	-1.4077945*
	(0.626292)	0.5603007	(0.5545922)	(0.5654750)
logcitation:AL	0.138910	-0.1183631	-0.1749044	-0.0778768
	(0.093230)	(0.1313764)	(0.1448796)	(0.1569097)
logcitation:AR	0.182103	-0.0261045	0.0222611	-0.1287407
	(0.180293)	(0.2337572)	(0.2288044)	(0.2572002)
logcitation:AZ	-0.337767***	-0.2220122**	-0.0613071	0.2184953*
	(0.067535)	(0.0749242)	(0.0942073)	(0.1083958)
logcitation:CO	-0.178129***	-0.1454761*	-0.1434657.	0.2116525*
	(0.049037)	(0.0618935)	(0.0787537)	(0.0924842)
logcitation:CT	-0.060732.	-0.1074110*	-0.2301093***	0.0029626
	(0.033009)	(0.0464564)	(0.0633208)	(0.0723735)
logcitation:DC	0.369309	-0.9270979***	-0.0683579	-0.3218818
	(0.227279)	(0.2612337)	(0.2794244)	(0.3201738)
logcitation:DE	0.010731	-0.1174470	-0.4652987***	0.0362808
	(0.067010)	(0.0872347)	(0.1155538)	(0.1310775)
logcitation:FL	-0.266654***	-0.3204439***	-0.0875794**	0.2860974***
	(0.043384)	(0.0540250)	(0.0689650)	(0.0778912)
logcitation:GA	0.143225**	0.2213397**	0.3190851	0.3821716***
	(0.047470)	(0.0708775)	(0.0978671)	(0.1146199)
logcitation:ID	0.556029***	0.8132211***	0.8409335***	0.3666455
	(0.095493)	(0.1736871)	(0.2245326)	(0.2582719)
logcitation:IL	-0.169534***	-0.2368320***	-0.3901584***	-0.1042973
	(0.025863)	(0.0354204)	(0.0462144)	(0.0559059)
logcitation:IN	-0.344338***	-0.2264409***	-0.2242623**	0.0456370
	(0.043624)	(0.0516671)	(0.0688337)	(0.0843313)
logcitation:KS	-0.651544***	-0.1155152	-0.5602753***	0.0537904
	(0.110949)	(0.1083372)	(0.1297889)	(0.1483599)
logcitation:KY	-0.194984**	-0.3652495***	-0.3097227**	0.1201849
	(0.067417)	(0.0893078)	(0.1147824)	(0.1387214)
logcitation:LA	-0.451501***	0.0152521	-0.0877889	-0.1920051
	(0.061412)	(0.0881597)	(0.1145658)	(0.1396741)
logcitation:MA	-0.130530***	-0.2095177***	-0.0532067	0.0473098
	(0.030540)	(0.0396127)	(0.0521332)	(0.0644304)
logcitation:MD	-0.300778***	-0.1471331*	-0.0487495	-0.1324554
	(0.053364)	(0.0626701)	(0.0792592)	(0.0880223)
logcitation:ME	0.344685*	-0.2464468	0.0713384	0.0437481
	(0.147063)	(0.2062558)	(0.2396454)	(0.2669693)
logcitation:MI	-0.244737***	-0.0451919	-0.0451892	0.1125947.
	(0.027135)	(0.0370529)	(0.0502371)	(0.0614853)
logcitation:MN	0.156486***	0.3887839***	0.3271007***	0.1808177*
	(0.031786)	(0.0441393)	(0.0608697)	(0.0750512)
logcitation:MO	-0.209778***	-0.2143415**	-0.3938213***	-0.3234710**
	(0.053587)	(0.0678309)	(0.0882212)	(0.1011904)
logcitation:MS	-0.565441*	0.2181438	-0.1990405	-0.4878046.
	(0.232210)	(0.2095339)	(0.2433522)	(0.2557133)
logcitation:MT	0.701526***	0.1473054	-0.0037319	-0.0606031
	(0.143103)	(0.3351083)	(0.3496200)	(0.3599819)
logcitation:NC	-0.056307	-0.0175105	0.2256668**	0.2507049*
	(0.049891)	(0.0629437)	(0.0825401)	(0.0975641)

logcitation:ND	0.230316	0.3327545	0.5854668*	-1.0238812**
	(0.191997)	(0.2369122)	(0.277684)	(0.3674600)
logcitation:NE	-0.085876	-0.3831806*	0.4446388*	-0.1724382
	(0.164458)	(0.1599524)	(0.2015836)	(0.2276499)
logcitation:NH	0.042011	0.3354757***	0.2312287.	0.6093428***
	(0.068120)	(0.1014577)	(0.1292639)	(0.1659282)
logcitation:NJ	-0.190372***	-0.3055734***	-0.4570489***	-0.0303649
	(0.024461)	(0.0353868)	(0.0487776)	(0.0557561)
logcitation:NM	-0.192065	0.0075928	0.5398087**	0.2184235
	(0.139083)	(0.1463717)	(0.1862095)	(0.2102913)
logcitation:NV	0.451324***	-0.7866662***	0.1076119	-0.7227219**
	(0.116069)	(0.1754912)	(0.2216726)	(0.2697158)
logcitation:NY	-0.297776***	-0.1736214***	-0.1459470**	-0.0450442
	(0.024297)	(0.0336147)	(0.0463659)	(0.0515394)
logcitation:OH	-0.056295*	-0.0979934**	-0.2392888***	0.1443210*
	(0.025536)	(0.0359355)	(0.0479040)	(0.0583039)
logcitation:OK	-0.169648***	-0.2144657***	-0.2754015**	0.1412511
	(0.037610)	(0.0631352)	(0.0894111)	(0.1088304)
logcitation:OR	0.527938***	0.2317676**	0.4453023***	0.1981449
	(0.064129)	(0.0873101)	(0.1044181)	(0.1253159)
logcitation:PA	-0.264351***	-0.1839366***	-0.3796501***	-0.0525337
	(0.025539)	(0.0351612)	(0.0475259)	(0.0559096)
logcitation:RI	-0.076908	0.4002672**	0.0062140	-0.2162214
	(0.108659)	(0.1487693)	(0.1846982)	(0.2012913)
logcitation:SC	-0.245904***	-0.1651836*	-0.1988624.	0.2369787.
	(0.060816)	(0.0836841)	(0.1114035)	(0.1336506)
logcitation:SD	-0.986236**	-0.2714250	0.3436002	-0.2654667
	(0.332105)	(0.2934377)	(0.4033604)	(0.4301360)
logcitation:TN	-0.229973***	-0.0696830	0.0486166	0.0803021
	(0.063634)	(0.0799568)	(0.1043054)	(0.1248744)
logcitation:TX	-0.040112	-0.0429290	0.0865895	0.1521441*
	(0.024654)	(0.0355285)	(0.0473675)	(0.0591909)
logcitation:UT	0.224740***	0.3713840***	0.1858961	0.4673686**
	(0.057491)	(0.0943717)	(0.1249638)	(0.1574636)
logcitation:VA	-0.015478	-0.1930025**	-0.2335331**	-0.0987736
	(0.045876)	(0.0664491)	(0.0827704)	(0.0991112)
logcitation:VT	-0.030757	0.8103115***	0.4633907*	0.7142725**
	(0.108284)	(0.1534527)	(0.1869523)	(0.2436633)
logcitation:WA	0.108415*	-0.1663545**	0.0128099	0.5034052***
	(0.048014)	(0.0617217)	(0.0766965)	(0.0913189)
logcitation:WI	0.154659***	0.0820082	0.1166705	0.1728811
	(0.037633)	(0.0523565)	(0.0670830)	(0.0832038)
logcitation:WV	0.102573	-0.2065112.	-0.0139195	0.1521379*
	(0.076741)	(0.1171806)	(0.1627062)	(0.1937660)
logcitation:WY	-0.142655	-0.1695261	-0.2290246	-0.3067336
	(0.195622)	(0.3685720)	(0.3980014)	(0.4467487)
Observations	109264	109264	109264	109264

Notes: McFadden's Choice Model —— Multinomial logit regressions. Robust standard errors clustered at the inventor level in parentheses. Regressions are based on the disambiguated inventor data (DID) described in Section 2.3 for the period 1977-1999. The data includes inventors located 51 states, where California is the base for the regression and is omitted in the regression. Personal income representing state-specific time trends are included as an alternative specific control variable. All columns indicating indicator variables for whether the inventor is in the top 1%, top 1-5%, top 5-10%, top 10-25% as ranked by quality and explained in the previous section. Observations are random sampling at 109264 root capacity. The results on constants are omitted here. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Predictions & Frequencies For Probabilities of Locating in States

	CA	AK	AL	AR	AZ	CO	CT
Prediction:	1.193e-01	6.406e-05	2.974e-03	7.596e-04	7.156e-03	1.295e-02	3.421e-02
Frequency:	1.19e-01	6.40e-05	2.97e-03	7.59e-04	7.15e-03	1.29e-02	3.42e-02
	DC	DE	FL	GA	HI	IA	ID
Prediction:	4.301e-04	6.525e-03	1.892e-02	1.317e-02	3.020e-04	3.477e-03	2.288e-03
Frequency:	4.30e-04	6.525e-03	1.892e-02	1.317e-02	3.020e-04	3.477e-03	2.288e-03
	IL	IN	KS	KY	LA	MA	MD
Prediction:	6.345e-02	1.678e-02	2.461e-03	6.342e-03	8.182e-03	3.964e-02	1.115e-02
Frequency:	6.345e-02	1.678e-02	2.46e-03	6.34e-03	8.1820e-03	3.96e-02	1.11e-02
	ME	MI	MN	MO	MS	MT	NC
Prediction:	1.089e-03	5.646e-02	3.163e-02	1.057e-02	5.399e-04	8.877e-04	1.252e-02
Frequency:	1.08e-03	5.64e-02	3.16e-02	1.05e-02	5.39e-04	8.87e-04	1.25e-02
	ND	NE	NH	NJ	NM	NV	NY
Prediction:	6.314e-04	9.975e-04	6.150e-03	8.610e-02	1.473e-03	1.748e-03	9.745e-02
Frequency:	6.31e-04	9.97e-04	6.15e-03	8.61e-02	1.47e-03	1.74e-03	9.74e-02
	OH	OK	OR	PA	RI	SC	SD
Prediction:	6.680e-02	2.482e-02	5.363e-03	7.123e-02	2.379e-03	8.337e-03	2.745e-04
Frequency:	6.68e-02	2.48e-02	5.36e-03	7.12e-02	2.37e-03	8.33e-03	2.74e-04
	TN	TX	UT	VA	VT	WA	WI
Prediction:	7.486e-03	7.075e-02	8.026e-03	1.448e-02	2.407e-03	1.253e-02	2.111e-02
Frequency:	7.48e-03	7.07e-02	8.02e-03	1.44e-02	2.40e-03	1.25e-02	2.11e-02
	WV	WY					
Prediction:	4.429e-03	6.772e-04					
Frequency:	4.42e-03	6.77e-04					

Notes: Table 3 compares the in-sample prediction of the current multinomial logit model and frequency of the top inventors. The dependent variable is the possibility for a top inventor located in each state, and independent variable is all the current variables available in table 3. The first row of the results summarizes the prediction of the possibility for a top inventor located in each state, the second row is the true frequency of the location for top inventors in the current sample.

Table 4: Correlation Coefficient on Quality Measures

	Dependent variable:		
	logcitation		logcount
	(1)	(2)	(3)
logcount	0.305***		
	(0.002)		
logmean		0.334***	-0.666***
		(0.002)	(0.002)
Constant	4.461***	4.515***	4.515***
	(0.007)	(0.006)	(0.006)
Observations	109,264	109,264	109,264
R^2	0.142	0.178	0.463
Adjusted R^2	0.142	0.178	0.463
Residual Std. Error (df = 109262)	0.541	0.530	0.530
F Statistic (df = 1; 109262)	18,075.110***	23,716.270***	94,259.780***
Note:			*p<0.1; **p<0.05; ***p<0.01

Notes: Table 4 shows the correlation of the different Quality and Quantity methods. The left column lists the independent variables and the top row lists the dependent variables. $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01

TABLE 6: ELASTICITY FOR STATES AND COUNTRY

STATE	ELASTICITYY	STATE MTR 1999	% CHANGE IN INVENTORS
CA	1.576267446	46.74	13.25938068
NY	1.661003409	44.95	13.03729317
TX	1.669489419	40.79	11.12232079
NJ	1.673355388	44.64	12.97680526
OH	1.705181227	45.15	13.48843374
PA	1.710126373	42.48	12.18511515
IL	1.71101385	42.6	12.24933964
MI	1.726390857	43.45	12.77975799
MA	1.746595324	44.38	13.40824782
MN	1.747674098	45.76	14.15533583
CT	1.75716412	43.51	13.03820565
WI	1.773565581	44.88	13.88296884
OK	1.780937606	44.33	13.64525095
FL	1.783006335	40.79	11.87858288
GA	1.785693937	44.52	13.78341271
WA	1.788920461	40.79	11.91798343
VA	1.789232219	44.31	13.69811147
CO	1.790719559	43.74	13.40747348
IN	1.791843996	42.84	12.94998587
NC	1.792340412	45.61	14.43305004
UT	1.797869264	44.4	13.81263501
MD	1.799628067	43.76	13.48472777
MO	1.801418708	44.46	13.87231471
OR	1.802244463	46.27	14.88794727
SC	1.803317046	45.06	14.21494538
AZ	1.80364351	43.77	13.52010736
DE	1.804032032	44.77	14.06116372
TN	1.804324221	40.79	12.02060497
NH	1.805041111	40.79	12.02538096
LA	1.807363819	42.96	13.12402239
KY	1.807857568	44.52	13.95448932
WV	1.810611864	44.71	14.07953765
ID	1.810916226	45.79	14.68460546
NV	1.811857531	40.79	12.0707927
IA	1.812042757	44.19	13.80792873
AL	1.812238216	42.59	12.96889667
VT	1.813648042	46.39	15.05170216
RI	1.814317442	46.69	15.23245501
KS	1.815171445	44.71	14.11499351
MT	1.815302912	45.11	14.33724037
ME	1.815746778	46.08	14.88981458
NM	1.815795769	45.89	14.78124564
NE	1.816510143	44.92	14.24125627
AR	1.816678783	45.14	14.36483059
ND	1.817112023	44.06	13.77643072
WY	1.817177955	40.79	12.10623794
DC	1.81735962	46.57	15.18758361
MS	1.817517606	43.85	13.66682891
HI	1.817899139	45.79	14.74122946
SD	1.81797458	40.79	12.11154514
AK	1.818179197	40.79	12.11290833
Country Elasticity:	1.710245152		

Notes: Table 6 summarizes the elasticities on State and Federal level. The first column displays the elasticity, while the second column presents the top 1999 MTR for each state. The last column calculates the percentage change in the number of inventors if there were a 10-percentage point reduction in the top tax rate from its actual level in each state in 1999.

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