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Taxation and Innovation in the 20th Century

Stefanie Stantcheva, Ufuk Akcigit, John Grigsby and Tom Nicholas

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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JEL Classification: H24, H25, H31, J61, O31, O32, O33

Keywords: Innovation, Income taxes, Corporate taxation, firms, inventors, state taxation, business taxation, R&D tax credits

Stefanie Stantcheva - sstantcheva@fas.harvard.edu
Harvard and CEPR

Ufuk Akcigit - uakcigit@uchicago.edu
University of Chicago and CEPR

John Grigsby - jgrigsby@uchicago.edu
University of Chicago

Tom Nicholas - tnicholas@hbs.edu
Harvard Business School

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Ufuk Akcigit John Grigsby Tom Nicholas Stefanie Stantcheva

March 24, 2021

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*Akcigit: University of Chicago, CEPR, and NBER (e-mail: uakcigit@uchicago.edu); Grigsby: University of Chicago (e-mail: jgrigsby@uchicago.edu); Nicholas: Harvard Business School (e-mail: tnicholas@hbs.edu); Stantcheva: Harvard, CEPR, and NBER (e-mail: sstantcheva@fas.harvard.edu). We thank Pol Antras, Julie Cullen, Jim Hines, Larry Katz, Henrik Kleven, Jim Poterba, Juan Carlos Suarez Serrato, Joel Slemrod, Ugo Troiano, Danny Yagan, Owen Zidar, Gabriel Zucman, Eric Zwick and seminar participants at UC San Diego, Duke Fuqua, Michigan, and NYU for comments and suggestions. We are deeply indebted to Jon Bakija for sharing his state-level personal income tax calculator. Akcigit acknowledges financial support from the NSF under Grant CAREER 1654719 and Sloan Foundation G-2018-11071. Nicholas acknowledges support from the Division of Research and Faculty Development at Harvard Business School. Stantcheva acknowledges support from the NSF under Grant CAREER 1654517. We thank Beatrice Ferrario, Helen Ho, Rafael Jimenez, Raphael Raux, and Simeng Zeng for excellent research assistance.

"On the one hand, taxation is an essential attribute of commercial society... on the other hand, it is almost inevitably ... an injury to the productive process."

Schumpeter, *Capitalism, Socialism, and Democracy* (1942), p. 198.

1 Introduction

Do taxes affect innovation? If innovation is the result of intentional effort and taxes reduce the expected net return from it, the answer to this question should be yes. Yet, when we think of path-breaking superstar inventors from history such as Wallace Carothers (DuPont), Edwin Land (Polaroid), or William Shockley (Bell Labs and Shockley Semiconductor) we often imagine hard-working and driven scientists, who ignore financial incentives and merely seek intellectual achievement. More generally, if taxes affect the amount of innovation, do they also affect the quality of the innovations produced, where inventors decide to locate and whether they work for firms or remain self-employed? Do corporate or personal income taxes play a bigger role?

Answers to these questions, while crucial to a clearer understanding of the impacts of taxation, have remained elusive due to a paucity of empirical evidence, especially over the long-run. Although the United States experienced major changes in its tax code throughout the twentieth century, we do not know how these changes influenced innovation at the individual, corporate or state levels.

In this paper, we bridge the data gap and provide new evidence on the impact of both personal and corporate income taxation at the individual inventor level and the state-level over the twentieth century. Our analysis leverages four historical datasets, two of which are newly constructed. First, we assemble a panel dataset on inventors from digitized patent data since 1920, allowing us to track inventors over time and observe their innovations, citations, place of residence, technological fields, and the firm (if any) to which they assigned their patents. Second, we combine the new inventor-level panel data with a new dataset on historical state-level corporate income taxes, compiled from a range of handbooks and reference works. Third, we incorporate a database on personal income tax rates from Bakija (2017). Finally, we use data on additional innovation-related outcomes, such as patent values from Kogan et al. (2017), and state-level value added, manufacturing share, average weekly earnings, establishment size, and total payroll from Allen (2004) and Haines (2010).

Our empirical analysis starts at the macro, state-level and then turns to the micro individual-inventor level. We provide a framework to link the micro-level responses to taxes to macro level aggregate elasticities. Individual inventors can respond to taxes by adjusting their time and resource inputs for innovation, by switching between the corporate and non-corporate sector, and by moving to another state. These responses can lead to changes in the quantity, quality, location, and sectoral composition of innovation. The observed macro-level elasticities will be the combination of all these micro-level responses.

For the interpretation of our results, note that inventors who work for companies ("corporate inventors") may react differently to taxes than individual "garage" inventors ("non-corporate") operating outside the boundaries of firms, as they face divergent incentives and may have distinct motivations. Also, the impact of corporate tax on individual inventors are the result of a complex chain of effects, including how taxes affect corporate income and firms' own tax responses, and how the surplus is shared between firms and inventors. Due to this complexity and the intricacies of the corporate tax code it is difficult to precisely capture the effective corporate tax burden that is relevant for inventors. Although our new data collection of detailed rates and tax base variables allows us to get much finer measures, our estimated corporate tax effects should be interpreted as reduced-form effects.

We implement several distinct and complementary strategies to identify the impact of taxes on innovation. First, we control for a detailed set of fixed effects, including state, year and, at the individual-level, inventor fixed effects, plus individual or state-level time-varying controls. Wherever possible, we exploit within-state-year tax differentials between individuals in different tax brackets (e.g., the top tax bracket versus the median one) and thus also include state $\times$ year fixed effects. These controls filter out other policy variations or the effect of contemporaneous economic circumstances in the state. Second, we use an instrumental variable approach which predicts the total tax burden facing a firm or inventor – which is a composite of state and federal taxes – using only changes in the federal tax rate, which are plausibly exogenous to any individual state's economic conditions. Finally, we use sharp tax changes in an event study design, and study the longer-run dynamic effects using distributed lag models.

Our findings can be summarized as follows. At the macro state level, personal and corporate income taxes have significant negative effects on the quantity of innovation, as captured by the number of patents, and on the number of inventors residing in the state. The elasticities range from 0.8 to 1.8 for personal net-of-tax rates and 1.3 to 2.8 for corporate net-of-tax rates, depending on how flexible time-varying state controls we allow for. The quality of innovation, as measured by the citations of patents, moves in proportion to the quantity, so that average quality is not significantly affected by taxation. The share of patents produced by firms as opposed to individuals is strongly negatively related to the corporate tax rate, with an elasticity around 0.6. Applying our framework to these estimates (in Section 5.6) confirms that these macro elasticities are consistent with the aggregation of the elasticities estimated at the individual-level.

At the individual inventor level, personal income taxes have significant negative effects on inventors' likelihood of having any patent or the number of their patents. They also influence inventors' likelihood of producing a highly cited patent or one that generates substantial value for the firm, but with small effects on the quality of the average patent. The elasticity of patents to the personal income net-of-tax rate is around 0.8, and the elasticity of citations is around 1. Corporate income taxes only shape the innovation output of corporate inventors rather than non-corporate inventors. The elasticity of patents of corporate inventors with respect to the net-of-tax corporate rate is 0.49 and that of their citations is 0.46.

We also find that inventors are significantly less likely to locate in states with higher taxes. The elasticity to the net-of-tax personal rate of the number of inventors residing in a state is between

0.10 and 0.15 for inventors from that state and 1.0 to 1.5 for out-of-state inventors, with an overall average mobility elasticity of 0.34. The corresponding elasticities for the corporate tax rate are 0.4 and 2.9, with an average mobility elasticity of 1. Corporate inventors' location choices are only responsive to the corporate income tax, with an elasticity of 1.25, whereas non-corporate inventors take into account both corporate and personal income taxes; their elasticity with respect to net-of-tax personal rates is 0.72 or 0.6 with respect to the net-of-tax corporate rate. In a nutshell, the state-level effects of the corporate response come predominantly from mobility responses, which are more likely to be zero-sum at the state level; while the effects of the personal income tax come from both mobility and innovation output responses.

Our paper contributes to several strands of the growing literature on the impact of taxes. With respect to migration decisions, Kleven et al. (2014) find very high tax elasticities of 1.6 of the number of high income foreigners in Denmark using a preferential tax scheme since 1992.[1] Kleven, Landais, and Saez (2013) find elasticities of 1 for foreign and 0.15 for domestic football players in the EU. Akcigit, Baslandze, and Stantcheva (2016) show that the international mobility of star inventors in response to top tax rates since the 1970s is significant, with an estimated elasticity of the number of foreign inventors of 1 and domestic inventors of 0.03. Cross-country elasticities are expected to be smaller than the cross-state ones estimated in this paper.[2] Most closely related are Moretti and Wilson (2014) and Moretti and Wilson (2017) which study the effects of state taxes on the migration of star scientists across US states, finding a high elasticity of 1.8 to personal taxes of the top 5% of inventors. We focus on a longer historical period, and on the less-studied corporate tax as another potential driver of the location decisions of inventors.

Our work also adds to the literature on the effects of state-level taxes on employment and business activity. On the personal tax side, Zidar (2018) studies how tax changes for different income groups affect aggregate economic activity and finds large elasticities to tax cuts for lower-income groups: a tax cut for the bottom 90% that amounts to 1% of state GDP results in around 3.4 percentage points of employment growth over a 2-year period, while the corresponding estimate for the top 10% is insignificantly different from zero. Tax changes for the bottom 90% percent have large impacts on both the extensive margin and intensive margin of labor supply, with a 1% of state GDP tax increase reducing labor force participation rates by 3.5 percentage points and hours by 2%. Keane and Rogerson (2015), reviewing the literature on micro and macro effects conclude that credible estimates of the macro-level compensated (Hicksian) elasticities are in the range of 0.5-1.0; in our case labor supply responses are only one of the several components driving innovation responses. Also informative is a comparison to the overall taxable income elasticities estimated in the literature for more recent decades (typically since the 1980s): 0.4 overall, and 0.57 for top earners in Gruber and Saez (2002); 0.30 in Giertz (2007); 0.35-0.97 in Moffitt and Wilhelm

[1]By contrast, Young and Varner (2011) study the effects of a change in the millionaire tax rate in New Jersey on migration and find small elasticities. Young et al. (2016) consider the migration of millionaires in the US using administrative data.

[2]Liebig, Puhani, and Sousa-Poza (2007) study mobility within Switzerland, across cantons and find small sensitivities to tax rates.

(2000); and 0.5-0.6 with appropriate controls in Saez et al. (2012). Patents and citations at the individual level seem to have elasticities that are of comparable magnitudes to these elasticities of taxable income overall.

Regarding state-level corporate taxes in the US, Suárez Serrato and Zidar (2016) quantify their incidence using a spatial equilibrium model and find large elasticities, as do we. They show that a 1% cut in business taxes causes a 3.35-4.07% increase in establishment growth over a ten-year period; a 3.74-4.28 increase in population growth, and a 0.78-1.45 percent increase in wage growth. Patel et al. (2017) find an elasticity of taxable corporate income of 0.9. Giroud and Rauh (2017) use establishment-level data to estimate the effects of state taxes on business activity (employment and the number of establishments) and find smaller effects. Our paper differs in the new data we use, the range of outcomes considered (patents, individual level mobility, and additional economic variables such as value added, employment, or income per capita), and the long time period.[3]

More closely related to innovation, Cullen and Gordon (2006, 2007) analyze the effects of personal income taxes' levels and progressivity on startup activity and risk-taking by entrepreneurs.[4] A related strand of this literature studies the effects of policies like R&D tax credits on innovation. Bloom et al. (2002) and Bloom and Griffith (2001) find a positive impact of these incentives on the level of R&D intensity over both short and longer time horizons. On the other hand, Goolsbee (2003) and Goolsbee (1998) argue that R&D tax credits mostly push up workers' wages. We always control for state-level R&D tax credits in our regressions.[5]

The rest of the paper is organized as follows. Section 2 provides a conceptual framework for linking micro individual-level and macro state-level elasticities. Section 3 describes the data and some key summary statistics. Section 4 outlines the state-level analysis, results, and robustness checks, while Section 5 focuses on the inventor-level analysis. Section 6 concludes.

2 Conceptual Framework: Micro and Macro Effects of Taxes on Innovation

We start with a simple framework to think about aggregation from the micro-level inventor elasticities to the state-level macro elasticities. Like other economic activities, innovation requires both

[3] In Section 4, we review further macro estimates based on federal-level variation, which tend to be large.

[4] Our work is more distantly related to numerous papers studying the origins of innovation at the micro-level. Recent contributions include Jones (2010) and Jones and Weinberg (2011), which show the effect of inventor age, Jones et al. (2008), which focuses on collaborations of inventors across universities, Wuchty, Jones, and Uzzi (2007), which considers the role of team production, and Jones (2009) on the growing trend towards specialization. Aghion et al. (2017) study the social origins and IQ of inventors in Finland. Bell et al. (2019) and Akcigit et al. (2017) study the parental backgrounds of inventors in the US on, respectively, modern data and historical data. Our data allows us to extend this literature by considering the impact of taxation over a long time period for a multitude of innovation outcomes (quantity, quality, and location) that arise from both inventor-level and firm-level behavior. Jones (2018) theoretically and quantitatively studies how to tax top incomes in a world of innovation and positive externalities from ideas.

[5] Using a regression discontinuity design based around firm size cutoffs for R&D tax subsidies in the UK, Dechezleprêtre et al. (2016) find significant effects of subsidies on both R&D spending and patenting.

time and material inputs to generate outputs, and personal and corporate income taxes can affect the net returns to these investments. At the individual inventor level, the main choice margins are i) the level of inputs (time and materials), ii) whether to operate in the corporate sector (by either incorporating or working for a company) or in the non-corporate sector (by being self-employed), iii) and which state to live in.[6]

The responses to taxes may differ for corporate and non-corporate inventors. First, firms supply a share of the inputs, in accordance with their own tax incentives, and these firm inputs could be complementary to inventors' inputs. Thus, firms make part of the decisions *in lieu* of inventors and are likely driven by net returns. The response to taxes for corporate inventors is capturing a mix of their own and their firm's responses. Second, how taxes filter through to the inventor's payoff depends on surplus sharing between firms and inventors and on the strength of performance-based pay (see Van Reenen (1996), Card et al. (2014), Aghion et al. (2018), and Kline et al. (2019)). Finally, corporate inventors can have different preferences and motivations than non-corporate ones, e.g., be mainly driven by economic net returns rather than scientific motivation.

Conditional on being an inventor employed by a firm, corporate taxes should not affect input decisions if innovation inputs, including effort, are all perfectly expensed. More generally, however, one would expect corporate taxes to not be neutral if there are unobserved inputs (for tax purposes), or if firms are credit-constrained and use their retained profits or earnings to finance subsequent innovation, or hire inventors. In addition, even if corporate taxes did not distort innovation inputs conditional on being employed by a firm and in a given state, they do affect the total net payoff from being a corporate inventor in that state. Thus, they can influence the (extensive margin) occupational, sectoral (corporate or non-corporate), and geographical location choices.

To capture these inventor-level responses to taxes, consider inventor i in state s and year t, who produces a quantity y_{ist} and a quality q_{ist} of innovation. Inventors can be in the corporate sector (c) or in the non-corporate (personal) sector (p); they can also be from state s (d for "domestic") or from another state (o for "out of state"). Let $I_t^{d,c}$ be the set of corporate inventors from state s who locate in the state at time t, $I_t^{o,c}$ be the set of out of state corporate inventors locating in s at time t, and $I_t^c = I_t^{d,c} \cup I_t^{o,c}$ the set of all corporate inventors in the state. Similarly, let the sets of non-corporate inventors be $I_t^{d,p}$ and $I_t^{o,p}$. $I_t^d = I_t^{d,c} \cup I_t^{d,p}$ is then the set of inventors from the state.

Innovation output depends on the total effective corporate and personal income net-of-tax rates (that combine federal and state level taxes) of inventor i if they chose to locate in state s, which we can write as:

$$y_{ist} = y_i(1 - \tau_{st}^c, 1 - \tau_{st}^p)$$

Denote by $\varepsilon_{Y,p}^c := \frac{d\log(y_{ist})}{d\log(1-\tau^p)}$ the innovation production elasticity of corporate inventors with respect to the net-of-tax personal rate $(1-\tau^p)$ and their elasticity with respect to the corporate net-of-tax rate by $\varepsilon_{Y,c}^c := \frac{d\log(y_{ist})}{d\log(1-\tau^c)}$. The corresponding elasticities for non-corporate inventors are $\varepsilon_{Y,p}^p$ and

[6] One margin of response which we will abstract from is the choice of becoming an inventor in the first place. By construction, the patent data only contains people who patent at least once.

$\varepsilon^p_{Y,c}$. The production of the quality of innovation may also depend on net-of-tax returns, i.e.:

$$q_{ist} = q_i(1 - \tau^c_{st}, 1 - \tau^p_{st}),$$

with elasticities $\varepsilon^c_{Q,c}$, $\varepsilon^c_{Q,p}$, $\varepsilon^p_{Q,c}$, and $\varepsilon^p_{Q,p}$.

We assume that the production of innovation elasticities can differ across corporate and non-corporate inventors, but are homogeneous within these groups.[7] These elasticities blend the possible behavioral responses outlined above, but also technological parameters of the innovation production function, such as how elastic innovation quantity and quality are to inputs. Imagine at one polar extreme, that testing twice the number of chemical compounds would lead to at least twice as many discoveries of new drugs; in this case, innovation quantity is very elastic to inputs. At the other extreme, recall the (fictitious) parable of Newton sitting under a tree, the apple falling, and innovation happening. This exemplifies a perfectly inelastic innovation production function. Quality as well may be highly elastic or, on the contrary, out of the control of inventors.

Inventors also choose which state to work in. Denote by $\eta^d_p := \frac{d\log(\int_{i\in I^d} di)}{d\log(1-\tau^p)}$ the elasticity with respect to the personal net-of-tax rate of the number of inventors from the state who reside in the state and symmetrically η^o_p the elasticity with respect to the personal net-of-tax rate of out-of-state inventors (who can potentially move into the state). Denote the corresponding migration elasticities with respect to the net-of-tax corporate rates by η^d_c and η^o_c.

At the state level, total innovation $Y := \int_{i\in I^d \cup I^o} y_{ist} di$ has an elasticity with respect to the net-of-tax rate $1 - \tau^p$ that can be expressed as a function of the inventor-level innovation production and migration elasticities:

$$\varepsilon_{Y,p} := \frac{d\log(Y)}{d\log(1-\tau^p)} = \gamma^c_Y \varepsilon^c_{Y,p} + (1-\gamma^c_Y)\varepsilon^p_{Y,p} + \gamma^d_Y \eta^d_p + (1-\gamma^d_Y)\eta^o_p \tag{1}$$

where $\gamma^c_Y = \frac{\int_{i\in I^c} y_i}{Y}$ is the share of innovation produced by corporate inventors in the state; $\gamma^d_Y = \frac{\int_{i\in I^d} y_i}{Y}$ is the share produced by inventors from the state. Similarly, the elasticity of innovation quality, as measured by, e.g., total citations, is:

$$\varepsilon_{Q,p} := \frac{d\log(Q)}{d\log(1-\tau^p)} = \gamma^c_Q \varepsilon^c_{Q,p} + (1-\gamma^c_Q)\varepsilon^p_{Q,p} + \gamma^d_Q \eta^d_p + (1-\gamma^d_Q)\eta^o_p \tag{2}$$

where $\gamma^c_Q = \frac{\int_{i\in I^c} q_i}{Q}$ with γ^c_Q the share of citations accruing to corporate inventors and γ^d_Q is the share of citations accruing to inventors from the state.

The macro effects of taxes on total innovation quantity and quality are thus due to the individual-level responses in innovation production and to the change in the number of innovators due to migration. The latter can be viewed as a form of cross-state spillovers, which, in some cases are

[7] While we could in principle allow for further heterogeneity, this is the most relevant heterogeneity that we can estimate in the data given our focus on corporate and personal tax rates.

zero-sum from the point of view of the US as a whole.[8] The higher the share of corporate patents or citations, the closer the macro-level elasticities are to those of corporate inventors. The more out-of-state inventors contribute to total patents or citations in a state, and the more the macro elasticity is driven by the in-migration elasticity from other states, i.e., by cross-state spillovers.

The elasticities of the total number of inventors in state s to the personal and corporate net-of-tax rate are simply:

$$\varepsilon_{\text{inventors},p} = \gamma^d \eta_p^d + (1-\gamma^d)\eta_p^o \qquad \varepsilon_{\text{inventors},c} = \gamma^d \eta_c^d + (1-\gamma^d)\eta_c^o$$

where γ^d is the share of inventors living in the state who are from the state. The elasticity of the share assigned is the elasticity of corporate patents minus the elasticity of all patents.

$$\varepsilon_{\text{share assigned},p} = \varepsilon_{\text{corporate patents},p} - \varepsilon_{Y,p}$$

Thus, if corporate inventors are more elastic to taxes than non-corporate ones, e.g., if they are more sensitive to net economic returns or more profit-driven, the share assigned would be increasing in the net-of-tax rate.

We start by estimating the elasticities for different innovation outcomes at the macro level, e.g.,, total patents, citations, total number of inventors, or the share of patents granted to companies. We then estimate their components separately at the micro level by disentangling the production elasticities and cross-state mobility elasticities. As we noted in the introduction and above, because the effects of the corporate tax on individual inventors is the result of a series of impacts, depending on how it affects corporate income and firms' own tax responses, and how the surplus is shared between firms and inventors, our estimated corporate tax effects should be interpreted as reduced-form effects. In Section 5.6 we show that the aggregation from the micro to the macro level works well quantitatively.

Dynamic Effects. The response to incentives for innovation can be dynamic. We will explicitly consider this possibility using event studies (Section 4.3) and distributed lag models (Section 4.4).

The latter suggests that, as one may expect, there is a lag between changes in taxes and changes in innovation outcomes because the process from the input stage to a finished innovation takes time. Some new innovation may simply require scaling up already existing inputs, which can happen very rapidly, e.g., providing existing highly-skilled R&D employees with more funding for experimentation. Yet, developing other innovations may require a much lengthier process of trial and error or adjusting scarce inputs sluggishly, e.g., having to find highly specialized researchers to hire. In our benchmark analysis, we will thus use three-year lagged tax rates relative to the application date of the patent. We also allow for a three-year window to measure individual-level

[8]There could be improvements in productivity from migration, if inventors move to more suitable places. In our analysis, we will control for the "goodness-of-fit" of an inventor with a given state. Yet, migration that arises from tax competition only is more likely to be zero-sum at the federal level.

innovation outcomes.

Importantly, innovation can also be forward-looking because the initial investment may pay off over a longer period. Forward-looking effects for tax responses will depend on the pattern of payoffs from the innovation, on whether a given tax change is considered to be short-lived or more persistent, and on how people form their future expectations about tax rates based on current tax rates. These are common issues for empirical studies of taxation related to forward-looking investments. We would expect lower elasticities to current or lagged tax rates – and, instead, possibly significant elasticities to leading tax rates, i.e., "pre-trends" – if innovation payoffs are more back-loaded, if agents are more forward-looking, and if future and current tax rates are less correlated. If people were able to forecast future tax rates well, we could expect the leads of taxes to matter significantly.

3 Data Construction and Descriptive Statistics

In this section, we describe the sources for, and the construction of, our new data. All the variables are defined sequentially throughout the text and in more detail in Appendix A.1.

3.1 Historical Patent Data and Inventor Panel Data

The starting point of our inventor panel data are the digitized patent records detailed in Akcigit, Grigsby, and Nicholas (2017) (hereafter, AGN). They contain information on almost every patent granted by the United States Patent and Trademark Office (USPTO) since 1836, including the home addresses of the first named inventor on each patent, the application year, and the patent's technology class. From 1920 onwards, the data also contain the name of every inventor listed on the patent document, and the entity to which the patent was assigned, if applicable.[9] Throughout our analysis, we assign a patent to a given year based on its *application* year rather than its year of eventual grant, as this is the date closest to the actual creation of the innovation.

The data contribution of the current paper relative to AGN is to transform these patent records into a panel at the inventor level, by "disambiguating" them using a machine learning algorithm that adapts and improves on the one in Lai et al. (2014). The full algorithm is described in Online Appendix OA.1, where we also report results from checking its performance manually, by looking for false positives and false negatives on a substantial subset of randomly selected records. Only around 1.5% of records appear to be incorrectly grouped together into one "inventor;" a similar share are incorrectly split when they appear to be the same inventor.[10]

[9]Using information on the inventors' name and location, AGN match these patent records to decennial federal censuses, which provide additional demographic information on inventors, and, crucially, their income levels in 1940.

[10]In addition, we have tested the sensitivity of our results to various alternative disambiguation routines, such as ignoring middle name or assignee (for which information is more sparse in early periods), using automatically generated training datasets or taking the Lai et al. (2014) disambiguation as a training dataset, shifting the threshold for two records to be considered as belonging to the same inventor, and introducing additional blocking rounds into the disambiguation. The core results of our paper are robust to these alternative disambiguation approaches. Our

Table A1 summarizes the results of our disambiguation algorithm and compares them with those of the benchmark for the modern period of Lai et al. (2014). Our disambiguation identifies 2.95 million US inventors who were jointly granted 5.3 million patents. There are 1.74 million US based inventors with a total of 2.78 million patents for our benchmark sample period 1940 to 2000.

We also merge in all pairs of cited-citing patents since 1947 (the year in which comprehensive citations of patents began), which we use to construct the total number of (forward) citations received by a patent until 2010. Citations are an often-used marker of the quality of an innovation (Hall et al., 2001; Trajtenberg, 1990). However, raw citation counts may be difficult to directly interpret as patent quality, for a variety of reasons, such as trends or differences across technological classes in the propensity to cite, and truncation of total citation counts for more recent years (i.e., more recent patents have had less time to accumulate citations). As a result, we adjust patents' citation counts following the quasi-structural procedure laid out in Hall et al. (2001).[11]

Because we know patent assignment status, we can allocate inventors to corporate and non-corporate categories following the assumption in Schmookler (1966) that non-assigned patents provides "a first approximation" for identifying independent inventors who were active outside of corporations.

We use patents as an outcome variable because they are a well-documented measure of innovation, even though their use involves some limitations. Based on nineteenth century data Moser (2005) found that the propensity to patent in the US could be low (at around 14% across industries) but rose significantly in industries like chemicals by the early twentieth century due to the threat of reverse-engineering (Moser, 2012, 2016). During the late twentieth century, Mansfield (1986) found that the vast majority of patentable inventions were actually patented – 81% in chemicals, for example, while recent data show extensive patenting in high-tech industries (Webb et al., 2018). Our analysis investigates the responsiveness of raw patent counts to tax changes, but we also look at quality-adjusted patents through their citations and market value. Hence, we are also able to isolate the responsiveness of patents that had the highest economic impact. We also study inventors (and their location), as well as a range of other economic outcomes described next.

Descriptive Statistics at the Inventor and State Level. Table 1 presents the core summary statistics for our sample at the individual inventor and state levels. Additional summary statistics on the control variables and additional outcomes used are in Table A2; more detailed moments of the distributions of inventor career lengths, patents, citations, and mobility of inventors in Table A3. Unless otherwise states, "citations" refer to our adjusted citation counts.

An inventor is considered "active" in any year between their first and last patent granted. 70% of active inventors have a patent in any given three-year span and the average number of patents per year is 0.68. 42% of inventors have at least 10 citations in any given three-year span. The average time span for which an inventor appears in the patent data is 3.3 years, but the distribution of

baseline disambiguation is the one that best balanced the false positive and false negative rates according to our tests.

[11] For more details, see Appendix OA.4.

career length is highly skewed, with a 95^{th} percentile of 15 years and a 99^{th} percentile of 33 years. The number of patents per inventor is also highly skewed, ranging from 2.6 patents over the lifetime for the average inventor to 25 patents for a top 1% inventor. Citations are even more concentrated: The median inventor receives 12.7 citations for their patents, but a top 1% inventor receives 890 citations during their career. Inventors also frequently work in multiple fields: the average inventor has patents in 1.6 USPTO technology classes and the most diversified top 1% of inventors have patents in 10 classes.[12] While most inventors remain in the same state for the duration of their careers, the highly mobile ones reside in three different states during their professional lives.

We also provide facts on the evolution of innovation over the twentieth century. Figure A1 depicts patents per 10,000 residents at the state level for each decade; Figure A2 shows inventors per 10,000 residents. The Northeast, the Rust Belt, and California appear as major innovation hubs early on. Patents per capita do not increase monotonically through time, and the 1970s recession can be observed here. In the 1990s and 2000s there is a large increase in patents per capita everywhere and an expansion of innovation regions. Figure A3 shows the share of corporate inventors and patents over time. Corporate patents are those patents assigned to corporations. Inventors are said to be corporate inventors in a year if they have at least one successful corporate patent application over the next three years. Despite fluctuations over time, the share of innovation attributed to the corporate sector has increased significantly over time.

3.2 Historical Data on Patent Value and Other Economic Outcomes

Although we focus on core historic measures of innovation, we present additional analysis on alternative outcome measures. First, we use the private patent value to a firm by Kogan et al. (2017), computed based on jumps in stock market value of the patenting firm around the time a patent is granted, which Kogan et al. find is strongly correlated with patent quality measured by forward patent citations. These data are available from 1926-2010 (with updates to 2019), and can be merged directly into our dataset of patents by their patent number identifier. By construction, however, these data only capture the value of patents produced by publicly traded companies. Since the share of patenting in corporations has changed drastically through time, as we just showed, we use this as a supplementary measure of innovation in this paper.

We add to these measures of innovation other broader economic outcomes, namely state-level data on manufacturing value added, total manufacturing payrolls, the share of workers in manufacturing, average weekly earnings and establishment size collected by Allen (2004).[13] These data are available annually from 1929 through 2013, and are mostly derived from Haines (2010), the County and City Data Book Series and the Census Bureau. Data on manufacturing aggregates, for

[12]The United States Patent Classification (USPC) system is maintained primarily to facilitate the rapid retrieval of every patent filed in the United States. The principal approach to classification employed today classifies patents based on the art's "proximate function." Patent classes may be retroactively updated as new technologies arise. We use the 2006 classification throughout this paper.

[13]We thank Price Fishback and Sam Allen for graciously sharing these data with us.

example, comes from the the United States Census of Manufactures. We also obtained a state-level personal income per capita series from the Bureau of Economic Analysis (BEA), which we use as a control for economic activity throughout our analysis. This series has been constructed by the BEA back to 1929 and captures the capacity of consumers to acquire goods and services.

3.3 Historical Personal Income Tax Data

We compute state-level personal income taxes from the detailed tax calculator provided by Bakija (2017), which incorporates most tax-relevant considerations such as federal tax deductibility, itemized deductions, and major tax credits.[14]

The evolution of personal income tax rates is described in Appendix A.2. First, Figure A4 reports the first year in which each state introduced a personal income tax, while Figure A5 shows the distribution of state personal income taxes over time. Most states began taxing personal income in the 1920s and 1930s. The number of states with a personal income tax increased sharply between 1920 and 1940, stagnated until the 1970s, when a number of additional states adopted this tax, and then remained stable thereafter. In the first years of introduction, state taxes mostly applied to very high earners, which is why we focus on the post 1940 period in our regression analysis.

Many states have progressive tax systems, although they are typically less progressive than the Federal system. States with especially progressive taxes are California, New York, and New Jersey. Five states – Connecticut, Indiana, Illinois, Michigan and Pennsylvania – instead have flat taxes. Florida, New Hampshire, Nevada, Tennessee, Texas, Washington and Wyoming never had a state personal income tax.

Construction of the Tax Measures. At the state level, there have not only been many personal tax rate changes, but also many frequent tax bracket changes. Because of these frequent changes in tax brackets, we compute total effective tax rates, combining state plus federal liabilities that apply to a single person who is at i) the median income and ii) the 90th percentile income of the national income distribution in any give year. Data on median income come from the Census Bureaus Historical Income Tables. Data on the 90^{th} percentile of incomes come from the World Inequality Database (Piketty and Saez, 2003). From the Bakija (2017) tax calculator, we compute the 90th percentile income MTR (denoted by MTR90); the 90th percentile income average tax rate (ATR90); the median income MTR (MTR50); and the median income ATR (ATR50). We use those measures in the state-level analysis in Section 4, and explain how we assign tax rates to each individual inventor in Section 5.

Key Tax Variation. Our empirical analysis makes use of the multitude of personal and corporate income tax changes that have happened since 1940. Appendix Figures A6 and A7 show the

[14] The data for Louisiana are unreliable between the years 1975 and 1982. We therefore drop Louisiana from our main analysis sample.

evolution of the marginal tax rates at the median and the 90th percentile income levels decade-by-decade.[15] Tax rates have followed very different trajectories across states–and have often also evolved differently from the federal tax rate.

Panel A of Figure A9 depicts the percent of states with a change in their statutory state-level taxes for each year, as well the mean size of the change, and the magnitude of the top 10th largest changes per year. The share of states changing their tax rate in any given year oscillates between 12-20% in the pre-1970s period and between 15 and 25%, or even up to 40% in the post 1970s period. The average tax change size fluctuates around 3-4 percentage points, but there can be many much larger changes of up to 17 percentage points.

Tax rates for a given percentile of the income distribution can change either because there is a reform in the federal tax code, a reform in the state tax code, or because the income distribution moves such that the percentile in question crosses the threshold into another tax bracket. Appendix Table A4 decomposes tax changes into these sources. Column (1) shows that 76.3% of tax rate changes for median earners and 78.3% of tax rate changes for 90^{th} percentile earners are accompanied by a change in federal tax liability, and, hence one-quarter of tax changes stem from purely state-level changes. Between 4 and 8% percent of tax changes for these percentiles result from changes in the income distribution in our sample.

3.4 Historical Corporate Income Tax Data

Federal and state corporate tax systems are complex and it would be very challenging to measure the effective corporate tax rate for innovating firms precisely, given the information we have on the firm side. Instead, we study the effects of corporate taxes on inventors and at the state level. Even then, there remain non-trivial measurement issues to get at the effective corporate tax incentive that are relevant for inventors. First, it is difficult to properly measure the tax incentives facing each firm that employs inventors because of firm-specific tax base variations due to deductions and tax credits, and the apportionment rules for multistate companies. Second, we would need a better appraisal of the share of the corporate tax burden that is shifted onto inventors. Our approach is as follows: To obtain the most precise measure of corporate tax burdens, we construct a state-level historical corporate income tax database covering approximately the period 1900-2016. It contains not only tax rates, but also a rich array of controls for historical state corporate tax bases that have been changing over time. We will also consider heterogeneous effects on corporate and non-corporate inventors, as they are likely to bear different loads from corporate taxes.

Corporate tax rate and base variables: We collect all corporate income tax rates and brackets, net income franchise taxes when applicable (since they are very similar to corporate income taxes), as well as any temporary surtaxes and surcharges levied on net income from a multitude of sources,

[15]Figure A8 illustrates the evolution of the top tax rate and the tax rate at the median income for a few highly inventive states, namely, California, Illinois, New Jersey, New York and Pennsylvania.

including detailed State Tax Handbooks and Legal Statutes.[16] We also collect additional state-level corporate tax rules from various State Tax Handbooks, state congresses, law reviews, and official reports. A full list of the sources used and data series construction are in Online Appendix OA.5.

We first gather detailed apportionment rules for multi-state companies going back to 1910. A company operating in multiple states must apportion its income across states to calculate its state tax liabilities. This is typically done based on where the firm's property, payroll, and sales are located. Appendix Figure A14 shows the evolution of these apportionment rules over time. We also assemble data on all other major state corporate tax base rules: the years a firm is allowed to carry forward or back losses, whether the state allows federal bonus depreciation or federal accelerated depreciation, or whether it allows an accelerated cost recovery system, whether the state has apportionment throwback rules, allows combined reporting, has a franchise tax, whether federal income taxes are deductible, whether the tax base is equal to the federal tax base, the rate of the investment and of the R&D tax credit, and how the R&D tax credits are applied (i.e., whether they are applied to an incremental base that is a moving average of past expenditures or whether they are applied on a base that is fixed on a level of past expenditures). We collect these data (except the throwback rule and the combined reporting rule for which early data were not available) for the period 1958-78, which we supplement with data from 1980 through 2010 from Suárez Serrato and Zidar (2018).

Construction of the Tax Rate and Base Measures. Our benchmark measure of corporate taxation will be the top corporate marginal tax rate, constructed using the top federal corporate tax rate and state and federal tax deductibility rules. Unlike personal income tax schedules, the state-levels corporate tax schedules most often simply have a (relatively low) threshold of exemption, below which the tax rate is zero and above which the top corporate tax rate applies.

To summarize the myriad tax base rules into a low-dimensional measure, we follow Suárez Serrato and Zidar (2018) in constructing an index of "corporate tax base breadth," which is larger if the tax base of a state in a given year is broader, as explained in detail in Appendix OA.2. State corporate tax revenues as a share of GDP are regressed on all tax base and apportionment variables, as well as state and year fixed effects. The index is the predicted value from this regression, excluding state and year fixed effects; it varies by state and year, and is standardized to have zero mean and unit standard deviation over our full sample. It may thus be interpreted as the number of standard deviations more revenue a state might expect to receive from a corporate tax increase given its tax base rules relative to a state with average tax base breadth. Since it is only available from 1958, we will control for it, but not in our benchmark regressions.

To address changes in the Federal corporate tax base, we use as a robustness check the series of effective federal corporate tax rates constructed by Auerbach and Poterba (1987) and Auerbach (2007) over the period 1959-2000 instead of the statutory federal tax rate.

[16]For example, we use HeinOnline Session Laws, HeinOnline State Statutes, ProQuest Congressional, Commerce Clearing House (State Tax Handbooks, State Tax Review), State Tax reports, Willis Report, Council of State Governments Book of States, and National Tax Association Proceedings.

Apportionment rules and multi-state inventors. Apportionment rules may also affect the interpretation of our estimated effects.[17] For single-state firms and inventors that have a nexus only in the state in which they reside, the corporate tax rate we use is precisely the relevant one. However, if an inventor works for, owns, or plans to start a multi-state company, the effective tax rate they face is correlated with, but not equal to, the in-state tax rate we control for. This will likely attenuate the effects of the corporate tax that we estimate. Controlling for the apportionment rules can alleviate part of this problem, as can our instrumental variable strategy below.

Other taxes. Our identification strategies should filter out alternative taxes that may otherwise impact our estimates. Ordinary, non-long-term capital gains are taxed as ordinary income and so are accounted for by our personal income tax measures. Long-term capital gains are taxed at a reduced rate at the Federal level, which is captured by year fixed effects. In a few instances, states have special treatments of long-term capital gains, which is captured by our state $\times$ year fixed effects. Dividends are typically taxed as ordinary income at the Federal level and in most states they are again captured by our personal income tax measures. States' sales taxes are absorbed by our state $\times$ year fixed effects. Finally, we always control for state-level R&D tax credits.

Overall, given the measurement issues, our estimates of the effects of corporate taxes at the individual inventor and at the state level are to be interpreted as reduced-form effects that mix in firms' and inventors' responses without being able to precisely estimate the effective tax incentive and the tax burden sharing between firms and inventors.

Descriptive Statistics on Corporate Taxes. We provide some descriptive statistics about the corporate tax system based on this new corporate tax database. Historically, many states had indirect corporate taxes, such as franchise taxes, imposed on corporations for the privilege of doing business in a state.[18] Over time, the share of states with direct corporate income taxes rather than indirect taxes has increased (see Figure A11).

Appendix Figure A12 shows the year in which corporate taxes were first introduced at the state level. Early adopters were Hawaii (1902), Wisconsin (1913), West Virginia, Virginia, and Connecticut (1915), as well as Montana and Missouri (1917). The latest adopters were Nevada and Michigan (1968), Maine and Illinois (1969), New Hampshire (1970) and Ohio and Florida (1972).

[17] Before the Uniform Division of Income for Tax Purposes Act (UDITPA) in 1957, different states had different ways of dealing with the taxation of multi-state companies. Although not all states adopted it, the UDITPA made these apportionment and allocation rules of the business income of multi-state companies more uniform, with a three-factor formula based on equal weights to the shares of a corporation's payroll, property, and sales in the state. In the past twenty years, the weight on sales has started to increase, which should arguably decrease the importance for a company of corporate income tax in states in which it has property and employment (but a low share of its sales).

[18] In several states, statutes make direct taxes unconstitutional and franchise taxes get around this problem. Some states have one or the other, sometimes both, but companies only pay one. Types of franchise taxes include taxes on net income (which are extremely similar to corporate income taxes and which we consider as such), Business enterprise tax (in New Hampshire), Gross receipts tax or commercial activity tax (which is the gross receipts tax in Ohio), Business and occupation tax (West Virginia, Washington, or Ohio, sometimes different for different industries), net worth/capital stock/asset value/shareholder equity combination taxes, or a value-added tax (Michigan's single business tax which is a franchise tax, not a sales tax).

Figure A13 shows the evolution of the top corporate marginal tax rates in all states, decade by decade. The number of states with a corporate tax increased sharply and then flattened completely after 1972. The mean state tax (conditional on having a tax) increased from around 3.5% in 1920 to close to 8% in the 1990s, and has declined slightly to above 7% since then. The median state had a non-zero corporate tax only since the late 1930s and it hovers around 6% today. States have had very different historical patterns of their corporate taxes, which is an advantage for our analysis.[19] The top 10% states ranked according to corporate tax levels each year saw their corporate tax rise from 2% in 1920 to around 10% today. The lowest 25% states never had a tax rate above 4%.[20] Finally, Figure A14 shows the time series of apportionment rules. Almost every state that has a corporate tax rate places at least some of the apportionment weight on the share of the firm's sales, property and payroll located there. The weight on sales in particular has grown in importance over time.

Key Corporate Tax Variation. Panel B of Figure A9 depicts the percent of states with a change in their top corporate tax rate, the mean size of the change, and the magnitude of the 90^{th} percentile largest change for each year. On average, one out of every 6 or 7 states faces a change in corporate tax in any given year; that share was much higher at one out of five in the 1970s and 80s. The mean tax change fluctuates around 1.5-2 percentage points, and the largest top 10% tax changes reach up to 6 percentage points.

4 The Macro Effects of Taxation

We begin with the effects of personal and corporate taxes at the state level over the period 1940-2000.

4.1 Benchmark Estimation

4.1.1 Macro-level innovation outcomes and specification

The main innovation outcomes at the state-year level are: (i) the quantity of innovation, as measured by the log number of patents produced during that year in the state; (ii) the quality of innovation, as measured by the log number of total adjusted forward citations ever received by the patents produced in the state that year; (iii) the log number of inventors residing in the state that year; (iv) the share of innovation produced by companies, as captured by the share of patents assigned i.e., inventors transferring patents to their employer through assignment rights. We consider

[19] For instance, California and New York were one of the relatively early adopters of a corporate tax and have followed similar patterns, with tax rates rising continuously before 1980, and experiencing stagnating levels thereafter. New Jersey was one of the late adopters but quickly brought its tax rate up to the same level as California and New York. Illinois also adopted a corporate tax quite late and kept it at a low and stable rate of close to 5% over time.

[20] The patterns summarized here, as well as the evolution of top corporate tax rates in a few select states, are also presented in Appendix Figure A11.

additional state-level outcomes in Section 4.1.3. Our baseline specification is:

$$Y_{st} = \alpha + \beta_p \ln(1 - MTR90_{st-3}) + \beta_c \ln(1 - \text{Corp. MTR}_{st-3}) + \gamma \mathbb{X}_{st-1} + \delta_t + \delta_s + \varepsilon_{st} \quad (3)$$

where Y_{st} is one of the innovation outcomes in state s and year t. $MTR90_{st-3}$ is the state's 3-year lagged personal income marginal tax rate at the 90th percentile of income and Corp. MTR_{st-3} is the 3-year lagged top corporate tax rate. δ_t and δ_s are sets of year and state fixed effects. $\mathbb{X}_{st}$ are time-varying state-level controls, namely, lagged population density, real personal income per capita, and R&D tax credits (lagged by 3 years, as are the other tax rates), intended to capture the effect of time-varying urbanization, economic activity, and R&D incentive programs. We use 3-year lags because of the dynamics visible in the event studies below, but we test the sensitivity to these specifications in Section 4.1.3. The benchmark regressions weight each state by its population in 1940, but we provide unweighted results as a robustness check as well.

The coefficients β_p and β_c are consistent estimates of the effects of personal and corporate taxes on innovation outcomes at the state-year level if, conditional on the controls, changes in state-level tax rates are not correlated with other policies or economic forces that affect innovation. Below, we will relax this assumption using an instrumental variable strategy.[21] Unless otherwise specified, standard errors of all state-level regressions are two-way clustered at the year and state × five-year bin levels. This accounts for arbitrary spatial correlation of errors within a year, as well as for serial correlation within states. In addition, we provide results with Newey-West errors of lag 10 below.

We can also allow for a more flexible specification, with state fixed effects that can vary over time. This helps absorb more of the other non-tax variation, such as contemporaneous economic policies or phenomena, which may otherwise be loaded on the tax coefficients. For instance, action to reduce taxes in a given state may go hand in hand with other business-friendly and innovation-fostering reforms, which could bias the estimated tax coefficients upwards. To do so, we estimate our core specification from (3) in long differences of 10, 15, or 20 years, i.e., for $k \in \{10, 15, 20\}$:[22]

$$\begin{aligned} Y_{st} - Y_{st-k} = {} & \beta_p[\ln(1 - MTR90_{st}) - \ln(1 - MTR90_{st-k})] \\ & + \beta_c[\ln(1 - \text{Corp. MTR}_{st}) - \ln(1 - \text{Corp. MTR}_{st-k})] + \gamma[\mathbb{X}_{st} - \mathbb{X}_{st-k}] + \tilde{\delta}_t + \tilde{\varepsilon}_{st} \end{aligned} \quad (4)$$

4.1.2 Results

Panel A of Table 2 shows the estimates from the state-level regressions in (3).[23] Each column represents one of the innovation outcomes Y_{st} described above. A one percent decrease in MTR90 (equivalently, a one percent increase in the net-of-tax retention rate at the 90th percentile) is associated with an approximately 1.8% increase in patents and inventors, and a similar 1.5% increase

[21] If the dependent variable Y_{st} is in logs, β_p and β_c are the elasticity of Y_{st} to changes in the net-of-tax personal and corporate tax rates. If Y_{st} is the share of patents assigned to a corporation, β_p and β_c are semi-elasticities.

[22] At the state level, state times year fixed effects would absorb all tax variation and cannot be included.

[23] Appendix Table A5 reports the coefficients on all control variables.

in citations. The corporate tax is also significantly correlated with innovation outcomes. A one percent lower top corporate tax rate is associated with 2.8% more patents, 2.4% more citations, and 2.3% more inventors. Given the similar responses of citations and patents – i.e., patent quality and quantity – to taxes, the average quality as measured by citations per patent exhibits a mildly negative, but not systematically significant response to taxes.

The share of patents assigned to companies (column 4) appears to be particularly sensitive to the corporate tax rate. A one percent increase in the top corporate tax rate is associated with close to 0.6 percentage points fewer patents assigned to companies. Appendix Table A6 shows that corporate patents are indeed more sensitive to the corporate tax than non-corporate patents, which explains the response of the share assigned to corporate tax changes. Conditional on the corporate tax, the share assigned is not significantly related to the personal income tax rate.

To take into account heterogeneous and time-varying corporate tax bases, Panel B of Table 2 controls for the corporate tax base index and its interaction with the top corporate tax rate. The main relationship between top corporate tax rates and innovation is largely unaffected by the inclusion of these controls, but states with broader corporate tax bases have larger elasticities of innovation to the corporate tax rate. For example, while the average state in terms of tax base breadth (index = 0) has an elasticity of patenting to corporate taxes of 2.4, a state with one standard deviation larger tax base index has an elasticity of 2.6.

Table 3 reports estimates from the long-difference specification in (4). As foreshadowed above, these estimates are smaller than the benchmark ones that have state and year fixed-effects only and become progressively smaller (while remaining significant) as the difference is taken over shorter time intervals. The elasticity of patents to the personal net-of-tax rate is 1.5 with the 20-year difference, 1.1 with the 15-year one, and 0.8 with the 10-year one. For citations the elasticities are 1.1, 0.7 and 0.6 and for inventors 1.5, 1.2 and 0.8 respectively. For the corporate tax, the corresponding elasticities are 2.0, 1.9, and 1.8 with 20-year long differences; 1.5, 1.2, and 1.3 with 15-year ones and 1.3, 1.0, and 1.2 with 10-year ones. The share assigned has a semi-elasticity of 0.4, 0.3 or 0.16 in these three long-difference specifications.

To visualize these results, Figure 1 plots binned scatters of log patents and log inventors against the log of personal and corporate net-of-tax rates. Both innovation and tax variables are residualized against state and year fixed effects as well as lagged population density, personal income/capita and R&D tax credits. Each dot corresponds to a percentile of the residualized tax rate distribution. There is a consistent log-linear relationship between tax rates and state-level innovation.

In Section 5.6, we discuss how these large macro elasticities are consistent with the aggregation of the micro-level elasticities estimated in Section 5. The magnitudes are also in line with the typically large macro-level elasticities estimated for other variables such as GDP in the US, at the federal level. Romer and Romer (2010) find that a 1% increase in the tax to GDP ratio at the federal level leads to a decline in real GDP between 2.5-3%, using a narrative approach to isolate exogenous federal-level tax changes (in Section 5.6 we discuss why federal-level elasticities could reasonably be expected to be smaller than state-level ones). Mertens and Ravn (2013) find that a one percentage point cut in the average personal income tax rate increases real GDP per capita by 1.4% on impact and by 1.8% after only 3 quarters. A one percentage point cut in the average corporate income tax rate increases real GDP per capita by 0.4% and up to 0.6% after 4 quarters. Mertens and Ravn (2014) find that a tax cut that lowers tax revenues by one percentage point of GDP increases GDP by 0.48% on impact and by 1.35% after two years. Lee and Gordon (2005) find an elasticity of GDP *growth* to corporate taxes of 0.18% in a panel of 70 countries over 1970-1997. Note that these are effects on GDP which can be viewed as the final "output" as a function of various inputs e.g., innovation inputs. Hence, it is expected that the effects of the factors that eventually contribute to GDP must also be quite elastic for them to translate into a high elasticity of GDP levels or growth.

4.1.3 Robustness checks and extensions

These results are robust to a variety of alternative specifications, controls, and sample restrictions, provided in Appendix A.3 and summarized here.

First, Table A6 shows the results for additional innovation and economic outcomes. Column (1) indicates that unadjusted citation counts respond similarly to taxes as do the adjusted citation counts. Columns (2) and (3) show that corporate patents respond more to corporate taxes than do non-corporate patents, but both respond similarly to personal taxes, which is consistent with the conceptual discussion in Section 2. The average stock market value of patents granted is strongly positively related to the top corporate net-of-tax rate with an elasticity of 1.8, but insignificantly related to the personal income tax rate at the state level, which is to be expected given that this measure only applies to publicly-traded companies. All other outcomes, i.e., average employment of manufacturing establishments, manufacturing value added, total manufacturing payroll, average weekly earnings, income per capita, and the share employed in manufacturing are all positively and strongly related to the corporate net-of-tax rate. The personal net-of-tax rate is positively associated with total manufacturing payroll, income per capita and the share employed in manufacturing, although the elasticities are consistently smaller than those with respect to the corporate rate. Thus, personal and corporate taxes exhibit a consistent correlation with other economic outcomes that can be expected to be related to innovation.

Table A7 shows significant, but less strong relationships between innovation and three other personal income tax measures: the marginal and average tax rates at the median income level and the average tax rate at the 90th percentile income level. Table A8 simultaneously includes the personal income marginal tax rates for both the median and the 90th percentile income levels and shows that the latter dominates. Overall, the association between innovation and our benchmark marginal tax rate at the 90th percentile is the strongest.

The core results are also robust to various other calculations of the tax rates, such as using the married tax rate (Table A9), itemizing deductions rather than taking the standard deduction if it is optimal to do so (Table A10), using effective federal corporate tax rates from Auerbach and

Poterba (1987) to compute our total corporate tax rate (Table A11), and changing the tax rate lag to one or two years (Table A12). Regarding standard errors, the results remain highly significant with Newey-West standard errors, allowing for serial correlation of the state-specific error terms for 10 years (Table A13).

The relationship between taxes and innovation also does not meaningfully change across a number of sample restrictions, e.g. dropping observations from the two largest and most innovation-intensive states – California and New York – in Table A14 or from a period with unusually low innovation – the 1970s – in Table A15.

The results are also robust to the inclusion or removal of additional control variables. Table A17 shows that controlling for state politics – specifically the share of a state's upper and lower houses that are Democrats and an indicator for having a Democratic governor – leaves the results largely unchanged (though the standard errors on personal tax rates are larger). Table A18 removes the controls for lagged population density and personal income per capita. Doing so leaves the estimated elasticity with respect to personal taxes largely unchanged, but increases the elasticity of patenting to corporate taxes. Finally, the results are not contingent on our choice to weight each state by their 1940 population, as Table A19 shows.

4.2 Instrumental Variable Strategy using Federal Tax Changes

Our OLS estimates may be biased if states set their taxes in response to their economic conditions or contemporaneously with other economic policies that affect innovation. To address this concern, we use an instrumental variable strategy that exploits changes in total personal and corporate tax burdens that are driven exclusively by changes in federal level taxes rather than state taxes and that is similar in spirit to the predicted tax burden in Gruber and Saez (2002). Specifically, the instrument used for the personal tax rate at a given income level in state s and year t is the tax that would apply if the income distribution and state-level personal tax rate did not change since a given year $t-k$ (where k is allowed to vary for robustness), but federal taxes were changing as they are in reality. Changes in the predicted tax are therefore driven purely by federal tax changes, which are likely exogenous to any given state's economic conditions and other state-level policies. The impact of federal tax changes varies by state and by income group based on the level of its state taxes (because of the state tax deductibility from federal taxable income) and on whether the state allows for federal tax deductibility.

Formally, denote by $\tilde{\tau}^c_{st}$ the corporate tax in state s year t and $\tilde{\tau}^{pj}_{st}$ the personal income tax at income percentile j in state s in year t. Let the corresponding federal level tax rates be τ^c_{ft} and τ^{pj}_{ft}.[24] Heuristically, ignoring complications of the tax code, the total tax rate on individuals with income at the j^{th} percentile who live in state s at time t is denoted by τ^{pj}_{st} and is equal to:

$$\tau^{pj}_{st} = \tau^{pj}_{ft}(1 - \tilde{\tau}^{pj}_{st}) + \tilde{\tau}^{pj}_{st}(1 - D^p_{st} \cdot \tau^{pj}_{ft}) \quad (5)$$

[24] Recall that we use tax rates at fixed income percentiles, rather than tax rates in fixed brackets, because tax brackets at the state level have changed extensively over time.

where D^p_{st} is an indicator variable equal to 1 if the personal income tax paid at the federal level is deductible from the state tax base in state s in year t. In practice, several states allow for the deductibility of federal taxes, and this has changed over time. Some key examples include California and New York throughout the 1940-2000 period, and Pennsylvania since 1971.

The instrument for the personal income tax of income group j in state s and year t, denoted by $\hat{\tau}^{pj}_{st}$, can be written (heuristically) as:

$$\hat{\tau}^{pj}_{st} = \tau^{pj}_{ft}(1 - \tilde{\tau}^{pj}_{st-k}) + \tilde{\tau}^{pj}_{st-k}(1 - D^p_{st-k} \cdot \tau^{pj}_{ft}) \tag{6}$$

where the actual state tax in year t is replaced by its lag $\tilde{\tau}^{pj}_{st-k}$ at time $t-k$, holding fixed the distribution of income as of $t-k$ when calculating the income of group j. Our benchmark specification sets $k = 5$, but the results are robust to alternative k. In practice, this instrument is calculated from the tax simulator, taking into account many layers of complexity of the state and federal tax code, as is done for the actual tax rate τ^{pj}_{st}.[25]

Similarly, the total corporate tax rate in state s and year t is:

$$\tau^c_{st} = \tau^c_{ft}(1 - \tilde{\tau}^c_{st}) + \tilde{\tau}^c_{st}(1 - D^c_{st} \cdot \tau^c_{ft}) \tag{7}$$

and we instrument it with the predicted tax burden holding state taxes fixed at their level in year $t-k$,

$$\hat{\tau}^c_{st} = \tau^c_{ft}(1 - \tilde{\tau}^c_{st-k}) + \tilde{\tau}^c_{st-k}(1 - D^c_{st-k} \cdot \tau^c_{ft}) \tag{8}$$

Figure 2 visualizes the source of variation in this instrument. The gray bars plot the change in the federal tax rate for the 90^{th} percentile (Panels A and B) and median (Panels C and D) earner in a given year. This change in federal taxes generates a change in the expected total tax rate faced by individuals in a state that varies based on pre-existing state tax laws. The blue dashed line in the figure shows the 90th percentile of the change in state tax rates as a result of this federal tax law change, while the black solid line plots the 10th percentile of this change. For nearly every federal tax change, there is visible variation across states in their induced tax changes. This is because states differ in their pre-existing tax rates $\tilde{\tau}^p_{st-k}, \tilde{\tau}^c_{st-k}$ and deductibility rules D^p_{st-k}, D^c_{st-k}. For an average federal tax change, the induced change in the personal income tax instrument has a cross-state standard deviation of 0.51 percentage points, and the 90-10 gap is 0.71 percentage points. The analogous numbers for the corporate tax instrument are 0.42 and 0.64 percentage points. Recall from Table A4 that 78% and 77% of personal and corporate tax rate changes, respectively have at least some federal component. As a result, it is unsurprising that the first stage is strong and significant (Appendix Table A20).

The IV results are in Panel C of Table 2. They are highly significant and slightly larger than the

[25] Note that even if states anticipate federal-level changes to some extent and adjust their tax policy accordingly, our instrument is computed using the state tax that applies at $t-k$ and for k sufficiently large, it is unlikely that states would have already adapted their state-level tax policy in anticipation of possible future federal tax changes.

OLS ones. One potential explanation for this magnitude may be that states are adjusting their tax rates in a counter-cyclical fashion, which would bias the OLS estimates downwards if innovation is pro-cyclical.[26]

4.3 Event Studies Around Large Tax Reforms

To provide visual evidence of the dynamic effects of taxes, we implement an event study analysis of large state tax changes, defined as those in the top 10% of state-level tax increases or the top 10% of tax decreases over the period 1940-2000. These correspond to state-level tax increases of at least 1.6 percentage points for the personal income tax and 2.75 percentage points for the corporate tax and to tax decreases of at least 0.9 percentage points for the personal income tax and 2 percentage points for the corporate income tax. On average, a large personal tax reform shifts the tax rate by 2.25 percentage points, which, given the mean total personal tax rate of 34% in the sample (Table 1), represents a 6.6% change. Likewise, an average large corporate tax reform shifts the tax rate by 4.1 percentage points, or 8.9% of the average total tax rate of 46%.

The estimation period covers the four years before and after each reform, for a total time span of 9 years, a span length chosen to be as large as possible, while also avoiding too many overlapping reforms.[27] We drop from the sample tax reforms which are preceded or followed by another tax reform within a four-year span. All tax changes are relabeled in the direction of tax increases.

For each reform, we construct a synthetic control state as the weighted average of other similar states that do not have a large reform in the 4-years before or after the focal reform following Abadie (2005). The weights are chosen to minimize the mean squared prediction error between treatment and synthetic control states in the four pre-reform years for log real personal income per capita, population density, and the dependent variable of interest (e.g., log patents). We then pool the reforms into one dataset and estimate the following regression:

$$y_{rst} = \alpha_r + \theta_r \times TREAT_s + \sum_{l=-4}^{4} \left[\beta_l + \gamma_l TREAT_s\right] \mathbf{1}\{t = l\} \quad (9)$$

where r indexes a reform, s is a state, t is the number of years since the reform, $TREAT_s$ is an indicator variable equal to 1 if state s is the treatment state and 0 if it is the synthetic control, and $\mathbf{1}\{t = l\}$ is an indicator for the observation corresponding to l years after the reform. α_r and $\theta_r \times TREAT_s$ are reform and reform-by-treated state fixed effects.

Figure 3 plots the set of γ_l, which represent the level of innovation outcome y_{rst} for the treatment state relative to the synthetic control state in relative year l. Time $l = 0$ is the first year during

[26]The correlation between corporate and personal tax increases and personal income per capita increases with a one year lag is indeed negative. Bloom et al. (2002) also find that innovation policies are countercyclical.

[27]Increasing the event window to be longer than four years necessitates dropping many large reforms due to the increased presence of overlapping reforms. Appendix Figure A15 plots the distribution of time between large tax changes at the state level. On average, states implement a large reform in the tax rate of personal and corporate income every 9 and 8.8 years, respectively.

which the new tax rate applies and the coefficients on the time indicators are plotted relative to the year before the new tax applies, $l = -1$. The upper row shows the effects of personal income tax changes; the bottom row the effects of corporate tax changes. The left column shows the effects on patents, the right column on inventors.

There is already a small negative effect of the taxes in the first calendar year of the tax change ($l = 0$). Consistent with the discussion of dynamic effects in Section 2 and with our use of 3-year lagged tax rates in the benchmark regressions, we can see that there is a lag in the effect of taxes on innovation. The strongest effects appear three to four years later, at which point states with a large increase in either personal or corporate taxes have roughly 12 to 15 percent fewer patents and inventors than similar states that did not experience a large tax reform. Given the average percent change in tax rates described above, this corresponds to a personal tax elasticity around 1.8-2.3 and a corporate tax elasticity of 1.3-1.7, both of which are in the ranges spanned by our OLS and long difference specifications.

Case Studies: We also investigate three special episodes of comprehensive tax reform in New York, Delaware, and Michigan. We again employ synthetic control techniques to provide sharp visual evidence of the effects of taxes on innovation. These results are in Appendix Section A.4 and Figures A16-A18. The progressively larger effects of taxes over time are clearly visible there too, with the gap between the treated and control states growing for several years after the large tax changes.[28]

4.4 Longer-Run Effects of Tax Changes

To study the longer-run dynamic effects of taxes, we use distributed lag models, which can disentangle the effects of different lags and leads of taxes. Specifically, we estimate regressions of the form

$$Y_{st} - Y_{st-1} = \delta_t + \sum_{l=-5}^{20} \beta_l [\ln(1 - T_{st-l}) - \ln(1 - T_{st-l-1})] + \Delta X'_{st-1}\nu + \epsilon_{st} \tag{10}$$

where $T \in \{MTR90, \text{Corp. Tax}\}$ is either the top corporate tax rate or the marginal personal income tax rate at the 90^{th} percentile income, δ_t is a year fixed effect, and X is a set of controls including personal income per capita, R&D tax credits, population density, and the non-focal tax rate (e.g. if T studies corporate taxes, we will control for personal tax rates). In addition, when studying corporate taxes, we include as controls a full distributed lag of the major tax base variables. Over this longer horizon, one might be more concerned about serial correlation in the error terms ϵ_{st} and we therefore cluster at the state level.

Figure 4 plots the cumulative effects $\mathcal{B}_l$ of a tax change in year t on innovation by year $t + l$,

[28] It is difficult to compute implied elasticities from these reforms as they changed both the corporate and personal income tax rates.

for $l \in -5, 20$, where $\mathcal{B}_l$:

$$\mathcal{B}_l = \underbrace{\left[\sum_{\tau=-5}^{l} \beta_l\right]}_{\substack{\text{Effect from } t-5 \\ \text{through } t+l}} - \underbrace{\left[\sum_{\tau=-5}^{-1} \beta_l\right]}_{\substack{\text{Renormalizing to be} \\ \text{relative to year } t-1}} \tag{11}$$

Consistent with our event studies, the figure shows that there are no significant, detectable pre-trends in innovation around tax changes. Note, however, that some pre-trends would be consistent with potential forward-looking effects of innovation, as discussed in Section 2.

Over the longer run, tax rate changes can have a sizable effect on innovation. The cumulative effect of personal tax rates grows over time and is on average equal to the OLS effect (which is estimated off a single 3-year lag of tax rates). After 20 years, a 1 percent increase in the net-of-personal tax rate is associated with an approximate 2 percent increase in total patenting (Panel A) or the number of inventors (Panel B). The average of the lag coefficients are 1.3 for patents and 1.1 for inventors. We find larger long-run effects for corporate taxes, at around 3-4%, but these are noisier and smaller effects cannot be convincingly ruled out. Overall, as emphasized in Section 3.4, measurement issues are much more constraining and make the estimated effects of corporate taxes noisier and less stable than those of personal tax rates.

5 Micro Level Effects of Taxes

In this section, we investigate the effects of taxes at the micro-level of individual inventors, considering what micro-level responses shape the macro elasticities outlined in the previous section.

5.1 Measures of Inventor Productivity, Tax Rates and Innovation Outcomes at the Individual Level

The general intuition behind our analysis at the individual inventor level is to use the variation in tax rates across inventors in the same state and year so as to be able to include state $\times$ year fixed effects, which account for other contemporaneous policy variations and economic circumstances affecting all inventors. To implement this strategy requires assigning inventors to their tax brackets. We do so based on their innovation productivity, which is strongly linked to inventor income. We also include inventor fixed effects.

Constructing Measures of Inventor Productivity. Previous work has demonstrated that inventor productivity, as measured by patents or citations, is strongly related to inventors' incomes. Using modern data, Akcigit, Baslandze, and Stantcheva (2016) show this link is strong for the eight largest patenting countries, as well as for Sweden and Finland. Bell et al. (2019) match IRS tax data to patent data for US inventors and also highlight the strong link between income and patenting. Using historical data, Akcigit, Grigsby, and Nicholas (2017) establish a link between patents and wages in their match between the 1940 Census and patent data. As our benchmark measure of inventor productivity in year t we use total patents produced until year t, but test sensitivity to this choice in section 5.3.1 below.

Measuring an Inventor's Tax Rate. Using this productivity measure, we can rank inventors nation-wide in each year t. We then call "high-productivity" inventors at time t those inventors who fall in the top 10% of the national productivity distribution in year $t-1$, and "low-productivity" inventors those who fall below that threshold. Since the distribution changes every year, this represents a dynamic ranking measure. However, it is highly persistent. 99.1% of the the inventors who are classified as being high-productivity ones in year t are still high-productivity in year $t+1$. Similarly, 98.9% of inventors who are classified as being low-productivity in year t are still low-productivity in year $t+1$.

We then assign effective personal income tax rates to each inventor depending on their rank. For our benchmark analysis, the effective personal income tax rate of an inventor at time $t-1$ is the state's tax rate for the 90th percentile individual at $t-1$, if they are in the top 10% of the productivity distribution in $t-1$, and the median tax rate otherwise. For left-hand side outcomes measured at time t, we use this lagged tax measured from time $t-1$. The estimated coefficients on this effective tax rate can be interpreted as intent-to-treat effects. The personal income tax rates at the 90th or median income are effectively instruments for an inventor's true tax rate and the regressions shown are the reduced-form ones of the outcome directly on the instrument.

Using just two groups and focusing on the tax rate at the median is not as restrictive as it may seem, because state schedules typically have few tax brackets. Nevertheless, we will show that our results are robust to using finer tax measures, different cutoffs, and alternative specifications.

Innovation Outcomes at the Individual Level. At the individual level, we consider the following outcomes to capture intensive and extensive margin responses on the quantity and quality of innovation, all measured over a three year window between, and including, years t and $t+2$:[29] (i) whether the inventor has any patent; (ii) whether the inventor has a successful patent with at least ten citations (which occurs for 41% of patents in our sample) (iii) how many patents the inventor has, conditional on having any (log patents); (iv) how many citations the inventor has, conditional on having any (log citations); (v) whether the inventor has a patent whose Kogan et al. (2017) value is higher than the median value of patents of all inventors active in that year.

[29] Recall that the year t refers to the application date, which is the date closest to the discovery of the innovation itself.

5.2 Identification

Let i index inventors and $s(i)$ be the state of inventor i. We first estimate the following fixed-effects specification

$$\begin{aligned} y_{it} = \alpha_i + \beta_p \cdot \ln(1 - \text{Personal MTR}) + \\ + \beta_c \ln(1 - \text{Corp. Tax}_{s(i)t-3}) + \gamma \mathbb{X}_{it-1} + \delta_{s(i)} + \delta_t + \varepsilon_{it}. \end{aligned} \tag{12}$$

where Corp. Tax is the top corporate tax rate in the state and the term $\ln(1 - \text{Personal MTR}) = \left[\chi_{it-1} \ln(1 - MTR90_{s(i)t-3}) + (1 - \chi_{it-1}) \ln(1 - MTR50_{s(i)t-3})\right]$ is the personal tax rate assigned to the inventor, according to the algorithm described above, where $MTR90$ and $MTR50$ are the personal income tax rates paid by the 90^{th} percentile and median individual in a state, and χ_{it} is an indicator variable equal to one if the inventor is high productivity. The controls in $\mathbb{X}_{st-1}$ include time-varying state-level covariates, namely, the state's lagged real personal income per capita and population density; as well as time-varying inventor-level controls, namely, the inventor's experience (years since the first patent) and its square, and an indicator for the inventor being high productivity (as described above). We include an inventor fixed effect α_i to filter out other individual-level heterogeneity.

We also add a state-inventor specific time-varying control, which is a measure of the agglomeration of innovation in the state, as captured by the number of patents applied for by other state residents in the inventor's modal technological class in the state in a year $t - 1$ (excluding the inventor's own patents), divided by 1,000. This agglomeration measure varies by state, inventor, and year, and it captures the fact that a given state in a given year may have varying degrees of attractiveness to inventors working in different fields. This could be, for instance, because the state has some specific amenities and infrastructure particularly well suited for innovation in that technology class. Inventors may also value being around others from the same field *per se*, if there are complementarities with other researchers, thanks to interactions or learning (Akcigit et al., 2018). It could also capture the negative effects of possible congestion, ideas stealing and competition from other inventors.

This first specification only has inventor, state, and year fixed effects, the advantage of which is that we can estimate the effect of corporate tax variation as well (which would be absorbed by the state $\times$ year fixed effects). Recall, however, from the conceptual discussion in Section 2 and the measurement issues outlined in Section 3.4, that the micro-level effects of the corporate tax rate are more indirect and reduced-form than those of the personal income tax rate. In addition, this specification may potentially lead to inconsistent estimates of the effects of taxes if there are other contemporaneous state-year level economic changes, or policies that covary with taxes and that also affect innovation.

Our second specification in (13) includes state $\times$ year fixed effects δ_{st} that absorb other contemporaneous economic developments or policy changes in the state, as well as corporate tax variation and changes in tax revenue and spending that can lead to investments in infrastructure and amenities conducive to innovation.

$$
\begin{aligned}
y_{it} = \alpha_i + \beta_p \cdot \ln(1 - \text{Personal MTR}) + \\
+ \beta_c \ln(1 - \text{Corp. Tax}_{s(i)t-3}) + \gamma \tilde{\mathbb{X}}_{it-1} + \delta_{s(i)t} + \varepsilon_{it}.
\end{aligned}
\tag{13}
$$

Here, $\mathbb{X}_{it-1}$ is the same as above, except removes controls for personal income/capita, R&D tax credits and population density, which do not vary within a state-year cell. Conditional on these controls and the state $\times$ year fixed effects, our estimated tax effects are consistent as long as there are no other simultaneous changes that differentially affect high productivity and low productivity inventors and that are systematically correlated with the effective tax rates. To relax this requirement, we also apply the same IV strategy as for the macro state-level regressions above and instrument for the total tax of an inventor who is in income group j (where j is either the 90th percentile or the median, according to our ranking of inventor's into tax brackets based on productivity) in state s at time t using $\hat{\tau}_{st}^{pj}$ from equation (6). With this strategy, we only require that the differential tax rate changes experienced by high and low productivity inventors in a given year and induced solely by federal-level tax changes, be uncorrelated with unobserved determinants of individual innovation.[30] Throughout the micro-level analysis, we use two-way clustered standard errors at the state and year level to allow for both serial and spatial correlation.

5.3 Results

Table 4 shows the benchmark results. The upper panel reports the estimates from the specification with state $\times$ year fixed effects in (13); the lower panel shows the specification with only state and year fixed effects from (12). The outcome variables listed in columns 1 through 5 are as defined in (i)-(v) above.[31]

The estimated effects of personal income taxes are very similar in the two panels, suggesting that the state $\times$ year fixed effects are not critical to the estimation. Focusing on the upper panel, a one percent higher tax rate at the individual level decreases the likelihood of having a patent in the next 3 years by 0.48 percentage points, which, given the mean probability of patenting (71%), translates into an elasticity of 0.68. On the intensive margin, conditional on having any patents or citations, a one percent increase in the personal tax rate is associated with a 0.8 percent decline in the number of patents (column 3) and a 1.1 percent decline in the number of citations (column 4). The elasticities are slightly smaller and equally significant conditional on state plus year fixed effects, namely 0.8 for the patent elasticity and 1.0 for the citation elasticity. The fact that the number of citations responds very similarly to the number of patents is consistent with the fact

[30] In specification (12) we can also instrument for the corporate tax using the predicted tax liability $\hat{\tau}_{st}^{c}$ from (8).

[31] For the indicator outcomes in columns 1, 2, 5, and 6, the coefficients can be interpreted as semi-elasticities to the net-of-tax rates. For the remaining columns, the continuous variables are all expressed in logs and the coefficients are elasticities to the net-of-tax rate.

(not shown) that the average quality (citations per patent) is quite inelastic to taxes and with the findings at the state level. Nevertheless, while on average patent quality is not strongly affected, the likelihood of having a high-quality patent decreases by 0.42 percentage points (relative to a mean of 42%) for every percentage point increase in the personal tax rate, which translates to an elasticity of 1 (0.9 with state plus year fixed effects). Similarly, a one percent increase in the net-of-tax rate is associated with a 0.26 percentage point increase (elasticity of 0.5) in the probability of having a high-value patent as measured by stock market value.

In the bottom panel, the effects of the corporate net-of-tax rate are consistently positive, but insignificant. Below, we show that this overall null effect masks heterogeneous impacts on corporate and non-corporate inventors as well as a sizable impact on inventors' mobility across states.

Table A24 presents the IV results at the individual inventor level.[32] They are very similar to and slightly larger than the OLS estimates.

5.3.1 Robustness and extensions

We provide robustness checks for each component of our strategy: productivity measurement, the ranking method, and on how we control for an inventor's tax rate.

Regarding the assignment of tax rates to inventors, we first use alternative cutoffs, e.g., allowing inventors in the top 5% or the top 25% be assigned the 90th percentile personal income tax rate (see Appendix Tables A26 and A27). Second, we can create finer groups with two or more cutoffs rather than just one. For instance, we assign the top 10% of the productivity distribution the tax rate at the 90th percentile of income, the top 10-25% of the productivity distribution the tax rate at the 75th percentile, and the median income tax rate to all inventors below the top 25% (see Appendix Table A28). The results also look very similar if we define inventor productivity according to their cumulative citation counts (Table A29).

Another way to perform this analysis would be to replace the effective tax rate measure in the regressions with a full set of interactions of the top state effective tax rate with indicators for the inventor's productivity rank (say, top 10%, top 10-25%, top 25-50%, etc.) as in Akcigit et al. (2016). The difference in the interaction terms of two groups (say the top 10% and the top 10-25%) gives the estimated effect of the top tax rate where the top 10% is the treated group and the top 10-25% is considered to be the control group. In reality, there are several possible control groups, ranging from closest (say, top 10-25%), which yields a lower bound of the effect of the top tax, to farthest (say, below top 50%), which yields an upper bound. The productivity of an inventor captures the propensity to be treated by the top tax rate. The results of this approach are reported in Table A30. The coefficients increase monotonically with the quality bin of the inventor, and give upper bound elasticities that are slightly larger than those in our baseline specifications.

The micro-level regressions are also robust to excluding California and New York (Table A31) or the 1970s (Table A32), to removing the controls for personal income per capita, agglomeration

[32] The associated first stage regressions are reported in Appendix Table A25.

forces and population density (Table A36), and using the tax rate for married couples instead of singles (Table A34). The results are also robust to excluding inventor fixed effects, but the results are noisier (Table A35).

The IV estimates are also robust to alternative constructions of the instruments. To address the concern that inventors endogenously change their location choice to respond to taxes, in Tables A38 and Table A39 we compute the tax rates instrument but using the tax rate of the inventor's home state (i.e. the state in which they first appear in the data), rather than that of their current state of residence. Thus, the instrument for an inventor of quality level j in year t who first appears in state s_0 is $\hat{\tau}^{yj}_{s_0t} = \tau^{yj}_{ft}(1 - \tilde{\tau}^{yj}_{s_0t-5}) + \tilde{\tau}^{yj}_{s_0t-5}(1 - D^{y}_{s_0t-5} \cdot \tau^{yj}_{ft})$, for $y \in \{c, p\}$ distinguishing between corporate and personal taxes. In all cases, the estimated coefficients are little changed from either the baseline OLS estimates or the core IV estimate.

Changing effects of taxes over time. The long time span of our data permit analysis of the potentially changing repercussions of taxes over time. Estimating equation (12) allowing for a differential impact of taxes for the periods before and after 1970 (Table A40) shows that the effects of both personal and corporate taxes on individual innovation have declined over time. This could be due to many forces, related to the innovation production function or to institutional features. On the former, shifting innovation amenities and the entrenchment of innovation hubs, may explain part of this evolution. Related to the latter, improved and enhanced individual or corporate tax optimization (which makes statutory rates less relevant), the overall reduction in federal personal income taxes, as well as the shifting of multi-state corporate taxation towards a sales-based apportionment could also have contributed.

Agglomeration effects. As discussed above, innovation relies on amenities and infrastructure, some of which are financed by tax revenue. We can use our measure of agglomeration that proxies for time-varying field and state-specific amenities and infrastructures interacted with inventors' personal tax rates in regression equation (12). We also control for total patent counts in the state, and total patent counts interacted with the effective personal tax rate in order to control for general (non-field specific) amenities at the state level. The results in Appendix Table A41 show that, whenever an inventor lives in a state where there is more innovation in their own technological field, their elasticities to taxes are smaller. Although our agglomeration measure is a coarse proxy for amenities, infrastructure, and innovation clusters, these results highlight that the total effects of taxes, including the value of amenities and spending that they fund are an important question to be explored further. A similar dampening of responses to taxes due to agglomeration will appear in the location choices of inventors in the next section.

5.4 Location Choice Model

To complete our analysis of the effect of taxation on innovation, we estimate a location choice model at the individual inventor level. Denote by $j[i]$ the tax bracket of inventor i, which we assign based on cumulative patent counts as in Section 5.1 (i.e., 90th income percentile bracket for high productivity inventors or median income bracket for everyone else). Suppose that the value to inventor i of living (and inventing) in state s in year t is:

$$U_{ist} = \alpha \ln(1 - ATR_{st}^{pj[i]}) + \beta_s \mathbb{X}_{ist} + \nu_{ist}$$

where ν_{ist} is an inventor-specific idiosyncratic value of being in state s at time t, $\mathbb{X}_{ist}$ are a set of detailed controls, and $ATR_{st}^{pj[i]}$ is the personal income average tax rate that would apply to inventor i in state s at time t were they to live there. If ν_{ist} is i.i.d with Type 1 extreme value, then the probability that an inventor locates in state s, denoted P_{st}^{i}, takes the multinomial form

$$P_{st}^{i} = \frac{\exp(\alpha \ln(1 - ATR_{st}^{pj[i]}) + \beta_s \mathbb{X}_{ist})}{\sum_{s'} \exp(\alpha \ln(1 - ATR_{s't}^{yj[i]}) + \beta_{s'} \mathbb{X}_{is't})} \tag{14}$$

which we can estimate using a multinomial logit regression.

For the sake of computational feasibility and for this estimation only, we restrict ourselves to the eight states which are both the among the fifteen most inventive states, as measured by total patents over the period 1940-2000, and have spells with a progressive state tax system (that is, 90^{th} percentile earners pay a higher marginal tax rate than do median earners). This sample restriction yields possible choice states of California, Maryland, Massachusetts, Minnesota, New Jersey, New York, Ohio, and Wisconsin. The regression contains the following controls: "Home State Flag" is a dummy equal to 1 if the state under consideration is the home state of the inventor, defined as the state in which they first patent; "Agglomeration Forces" is, as above, total patents granted to inventors other than i in state s in year t in inventor's i's modal technology class; interactions of the home state indicator and the agglomeration measure with the high productivity indicator; a quadratic of the experience of the inventor, interacted with state fixed effects (to allow experience to have different impacts in different states). "Assignee has Patent in Destination" is an indicator equal to one if the employer of the inventor already has had one patent in the state under consideration. In regressions which include only state plus year (rather than state $\times$ year) fixed effects, we control for the corporate tax base index, personal income per capita, population density, R&D tax credits, and the corporate tax rate, all lagged by one year. Since location choice decisions plausibly respond more quickly to tax changes, we lag all independent variables by one year in this exercise. In this inventor-level analysis, we are most concerned with cross-state location decisions within a given year, and because the computations are very demanding, we prioritize arbitrary spatial correlation in error terms by clustering at the year level.

Column 1 of Table 5 shows the specification with state plus year fixed effects; all other columns include state $\times$ year fixed effects, making use of the same logic for identification as explained above.[33] The coefficients represent changes in the log-odds ratio of locating in state s associated

[33] In columns with state $\times$ year fixed effects, only state-years with progressive personal taxes are included, as the

with a one unit increase in the independent variable; as these are difficult to interpret, the bottom rows show the elasticities of the number of inventors residing in a state implied by these coefficients. They are calculated following the method in Kleven et al. (2013) and Akcigit et al. (2016), summarized in Appendix A.2.

The personal net-of-average tax rate in a state is strongly negatively correlated with inventors choosing to locate there. The effect of taxes in column 2 is even stronger after absorbing state-by-year varying factors, suggesting that there are other attractive forces or policies in a state that may be correlated with tax rates and that need to be filtered out. With state $\times$ year fixed effects, the elasticity to the net-of-tax rate of the number of inventors residing in a state is 0.10 (standard error 0.04) for inventors who are from that state and 1.05 (standard error 0.45) for inventors not from that state, with an average elasticity of 0.32 (standard error 0.14). In the introduction, we discussed that these estimates are close to existing ones in the literature for the modern period.

Corporate taxes also have an important impact on the location choices of inventors. Column 1 shows that the elasticity of location choices to the net-of-tax corporate tax rate is, on average, 1.02 (standard error 0.18).

As expected, there are two strong pull factors – other than taxes – which strongly influence the location decisions of inventors. These are, first, the home state. Inventors are, like most other people, much more likely to remain in their home state than to move. Second, agglomeration forces are essential as well and increase the appeal of a potential destination state. Furthermore, as was the case for the inventor-level innovation decisions above, agglomeration influences not only the value an inventor derives from being in a state, but it also dampens the elasticity to taxes, as shown by the interaction term in column 3. This means that a state with higher levels of agglomeration in one's technology field will be able to attract more inventors even at the same tax burden than a state with lower levels of agglomeration.

Column 4 adds an interaction of the personal average tax rate with the indicator for whether the assignee that the inventor works for already has a patent in that state. This also makes the inventor less sensitive to taxes in that state, which could be either because of career concerns or lower frictions of moving to a state where the employer already has a physical presence.

5.5 Corporate Inventors

Although Table 4 shows that, on average, inventors do not adjust their innovation in response to the corporate tax rate, this may mask heterogeneity in the response to corporate taxation of corporate and non-corporate inventors. We thus re-estimate equation (12) interacting corporate and personal income tax rates with indicators for whether the inventor is a corporate or non-corporate inventor. As above, an inventor is defined as a corporate inventor in year t if they have at least one patent

others' taxes are absorbed in the state $\times$ year fixed effects.

assigned to a company over the next three years. Specifically, we estimate

$$\begin{aligned} y_{it} = \alpha_i &+ \ln(1- \text{ Personal MTR}_{s(i)t-3}) \cdot [\varepsilon^c_{y,p} C_{it} + \varepsilon^p_{y,p}(1 - C_{it})] \\ &+ \ln(1 - \text{Corp. Tax}_{s(i)t-3}) \cdot [\varepsilon^c_{y,c} C_{it} + +\varepsilon^p_{y,c}(1 - C_{it})] \\ &+ \nu \mathbb{X}_{it-1} + \delta_{s(i)} + \theta_t + \upsilon_{it} \end{aligned} \tag{15}$$

where C_{it} is an indicator equal to 1 if the inventor is a corporate inventor in year t, υ_{st} is an error term, and every other variable is as described in equation (12). Included in the $\mathbb{X}_{ist-1}$ are the earlier set of controls, as well as the corporate inventor indicator C_{it}, also interacted with the corporate tax base index by bins and with the indicator of being high productivity. The coefficients of interest are $\epsilon^c_{y,p}, \epsilon^p_{y,p}, \epsilon^c_{y,c}$ and $\epsilon^p_{y,c}$ which report the separate response of an innovation outcome to personal and corporate taxes, for corporate and non-corporate inventors.[34]

Table 6 reports the estimated elasticities for corporate and non-corporate inventors separately. Patents produced by corporate inventors have a significant and large elasticity to the corporate net-of-tax rate of 0.49. The null effect for the sample as a whole arises because, on the contrary, the innovation output of non-corporate inventors shows no statistically significant response to the corporate tax. The personal net-of-tax rate, however, strongly influences the patenting activity of non-corporate inventors, and to a lesser degree that of corporate inventors.

The quality of innovation as well responds differently across the two groups of inventors. Corporate inventors' likelihood of having any citation is unaffected by the personal net-of-tax rate, but significantly increased by the corporate net-of-tax rate. The opposite applies to non-corporate inventors. Overall, the average quality of corporate inventors is again insensitive to taxes, while that of non-corporate inventors is somewhat negatively affected by personal and corporate taxes, i.e., citations respond less positively than patents for the personal net-of-tax rate, and even negatively for the corporate net-of-tax rate. The latter point suggests that when corporate taxes are lower and corporate patents are more highly cited, this may come at the expense of non-corporate innovation being cited (a "crowding out" of citations), perhaps because corporate inventors tend to cite other corporate inventors more.

Turning to mobility, corporate inventors do not significantly adjust their location choices in response to personal taxes, but appear highly elastic to the corporate tax rate. The elasticity of corporate inventors' location choices to the corporate tax is 1.25. The location choices of non-corporate inventors respond strongly to both corporate and personal tax rates, with an elasticity of 0.72 to the personal tax and of 0.60 to the corporate tax.

On balance, the small and insignificant effect of corporate taxes on non-corporate inventors and their strong significant effects on corporate inventors' innovation contributes to the positive

[34] In order to estimate the differential effect of corporate taxes on innovation for corporate and non-corporate inventors, we only report estimates from regressions including state plus year fixed effects here, but as is clear from Table 4, the estimated personal tax elasticities do not change much between this specification and the one with state × year fixed effects.

insignificant effect for the full sample in Table 4. The fact that lower corporate taxes tend to stimulate corporate innovation more than non-corporate innovation is consistent with the large and significantly negative effect of corporate taxes on the share of patents assigned to corporations at the state level (Table 2).

5.6 Aggregating Micro to Macro

We can now show that the estimated micro-level responses are consistent with the macro-level ones. Before doing so, it is worth pointing out that, although the aggregation in Section 2 holds formally rue, there can in practice be a gap between the estimated macro elasticities and the aggregated micro ones because of the identification strategies, whereby the micro estimation controls for more time-varying and fixed state and inventor-level characteristics. Taxes can have effects on the market size and demand and, hence, general equilibrium effects on prices, wages, and interest rates, among others, due to the inflow of resources or knowledge from other states, i.e., cross-state spillovers other than through the inventor migration responses. In the macro estimations, state and year fixed effects will not filter out these general equilibrium effects. The long-differences estimations in Table 3, which allow for time-varying state fixed effects, are better at accounting for these effects and indeed yield smaller elasticities. The micro-level estimations including state $\times$ year fixed effects, or the agglomeration measure, control for such state-level time-varying price effects.[35]

Furthermore, at the macro level, the estimated effects of taxes are also determined by the composition of the inventor pool, in terms of their productivity, the sectors they work in, or whether they are corporate or non-corporate. In the micro regressions, these are filtered out to a large extent by our array of individual-level controls, including the inventor fixed effects or the indicator for being high productivity, as well as by the "agglomeration" measure which captures how well the inventor's field is doing in this location and proxies for general equilibrium effects at the tech class-state-year level. In addition, we cannot estimate the individual-level tax elasticities of becoming an inventor in the first place. That margin of adjustment, however, will contribute to the macro-level estimates.

These gaps may be particularly important for the corporate tax, which also shapes firms' behaviors and may not be well captured in the micro-level elasticities, but will appear in the macro-level ones. As discussed in Section 3, the corporate tax also poses specific measurement

[35]To see this formally, consider that each inventor's output is a function also of prices, wages, and other state-level variables $\mathbb{P}$, which are themselves functions of taxes, i.e., $y_{ict} = y_i(1-\tau^p, 1-\tau^c, \mathbb{P}(\tau^p, \tau^c))$. In this case, the macro-level estimated responses are due to direct responses to taxes and indirect responses that occur through general equilibrium effects:

$$\varepsilon_{Y,p} = \gamma^c \int_{i\in I^c} \left(\frac{dy_i}{d(1-\tau^p)} + \frac{dy_i}{d\mathbb{P}} \frac{d\mathbb{P}}{d(1-\tau^p)} \right) + (1-\gamma^c) \int_{i\in I^p} \left(\frac{dy_i}{d(1-\tau^p)} + \frac{dy_i}{d\mathbb{P}} \frac{d\mathbb{P}}{d(1-\tau^p)} \right) + \gamma^d \eta_p^d + (1-\gamma^d)\eta_p^o$$

The micro-level estimates will only isolate the first term in the brackets as the state $\times$ year fixed effects and the time-varying inventor-level controls will filter out many or most the general equilibrium effects going through $\mathbb{P}$. Thus, while the decomposition in Section 2 is accurate, the fact that identification does not come from the same variation at the micro and macro levels introduces a wedge.

issues, including for multistate inventors and firms, and its effects will not be as precisely estimated as those of the personal income tax. Finally, the identification at the micro inventor-level is less sharp for the corporate tax, as we cannot rely on within state $\times$ year tax variation by income tax brackets, as we do for the personal tax.

These considerations aside, we can use the formulas in Section 2 to aggregate the estimated micro-level elasticities and check their plausibility. Taking the elasticity of patenting with respect to personal tax rates for corporate ($\varepsilon^{c}_{Y,p}$) and non-corporate inventors ($\varepsilon^{p}_{Y,p}$) from Table 6, the location choice elasticities η^{d}_{p} and η^{o}_{p} from Table 5 for inventors from the state (home-state) and those not from the state (non-home state), and the share of patents accounted for both by corporate inventors and home-state inventors (γ^{c} and γ^{d}) from Table 1, the macro elasticity of patents implied by equation (1) is 1.77. This is very similar to our benchmark macro elasticity of 1.80 using OLS in Table 2, and slightly above the elasticities estimated using our long-differences specification, which range from 0.78–1.45 (Table 3). Repeating the same exercise for corporate taxes gives an implied macro elasticity of patents to corporate taxes of 1.08. This is smaller than the OLS estimate of 2.76, but is close to the range we estimate in our long-difference specifications (1.32–1.98).

Aggregating citation elasticities in this way also generates similar elasticities to the macro regressions. The implied macro elasticities of citations to personal and corporate net-of-tax rates are 1.28 and 1.15, respectively. These numbers are smaller than the baseline OLS estimates of 1.52 and 2.38, and around the range of our long-difference macro elasticities from Table 3, where personal tax elasticities range from 0.56 to 1.1, and corporate tax elasticities span 0.97 to 1.88.

These results suggest that almost all of of the macro elasticity of innovation to corporate taxes comes as a result of the changing location of innovation. This may be driven by firms' choices, rather than those of inventors. Individual innovation outputs do not appear to respond much to corporate taxation, subject to the caveats in properly measuring corporate tax burdens explained throughout. In contrast, the majority of the macro effect of personal taxation appears to result from reduced innovation at the individual level, rather than through shifting the location of innovation from one state to another.

We can extend this analysis at the federal level and compare the federal-level elasticities to the micro-level and state-level ones. At the federal level, we should recover the micro-level effects of taxes on patents and innovation quality. Cross-state spillovers, such as those due to the migration of inventors from one state to another, should not be reflected in the federal-level elasticities as they are, to a first-order, zero-sum across states. If these migration responses account for a large share of the overall tax response, there could be a significant wedge between the federal and state-level elasticities.

We estimate time-series regressions of aggregate US innovation on federal tax rates. We use the Auerbach and Poterba (1987) effective corporate tax rates for this exercise in order to capture federal-level corporate tax base changes. The results are reported in Table A23, which shows that the federal-level elasticities of patents, citations, inventors, and the share assigned to the personal net-of-tax rate are very close to the state-level macro elasticities, which makes sense as the migration responses are not the only driver of the responses to personal taxes. On the other hand, the corporate tax elasticities are much smaller, and closer to the micro-level ones. This is consistent with the fact that some of the major effects of corporate taxes are due to cross-state spillovers in terms of migration which are close to zero-sum at the federal level.

6 Conclusion

In this paper, we study the effects of personal and corporate income taxes on innovation in the United States during the twentieth century using a series of newly constructed datasets. At the state level and at the individual inventor level, personal and corporate taxes shape the quantity and the location of innovation. The micro-level elasticities aggregate up to yield relatively large macro elasticities that are substantially affected by cross-state spillovers due to inventors moving. Our empirical evidence provides a sense of how firms and inventors respond to the net return to innovation, and not only to tax rates, which are merely a component of that economic calculation.

In future work, it would be fruitful to compare the US experience to other countries, historically and contemporaneously. That would require a major data collection effort, as we have completed for the US, but our analysis highlights the benefits of such investments. While we have undertaken a systematic comparison of the state-level and federal-level effects, more needs to be done to estimate the effects of taxes on innovation at the national level in the US, when taking into account the international mobility of inventors, firms, and intellectual property. An answer to that question is central to a fuller understanding of a tax regime's real impact.

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Table 1: Summary Statistics

	Mean (1)	S.D. (2)	1940-59 (3)	1960-79 (4)	1980-99 (5)
Inventor-Level Data: Outcomes					
# annual patents	0.684	1.103	0.633	0.650	0.727
Pr{Has patent in 3 years}	0.703	0.457	0.661	0.700	0.723
# annual citations	16.9	98.7	5.6	7.1	27.7
Pr{Has 10+ citations in 3 years}	0.418	0.493	0.298	0.342	0.516
Inventor-Level Data: Taxes					
Personal marginal tax rate (MTR)	0.226	0.077	0.162	0.239	0.246
Corporate MTR	0.455	0.079	0.417	0.521	0.431
N (millions)	6.212	.	1.323	1.850	3.039
State-Level Data: Unlogged Core Outcomes					
# Patents (000s)	1.02	1.62	0.75	0.97	1.35
# Inventors (000s)	1.07	1.79	0.65	0.98	1.59
# Citations (000s)	20.99	63.32	6.67	10.32	45.99
Share Patents Assigned to Corporations	0.66	0.18	0.53	0.71	0.74
State-Level Data: Taxes					
90^{th} Percentile Income MTR	0.34	0.10	0.23	0.38	0.40
90^{th} Percentile Income State MTR	0.04	0.03	0.02	0.04	0.05
Median Income MTR	0.22	0.05	0.18	0.24	0.23
Median Income State MTR	0.03	0.03	0.01	0.03	0.05
Ratio of 90^{th} to Median Income State MTR	1.58	0.34	1.32	1.60	1.80
Corporate MTR	0.46	0.07	0.45	0.51	0.42
State Corporate MTR	0.05	0.03	0.03	0.05	0.07
R&D Tax Credit (percentage points)	0.46	1.93	0.00	0.00	1.37
Observations	2880	.	960	960	960
Sample Composition					
% Corporate Patent	0.861	.	0.751	0.860	0.902
% Home-State Patent	0.860	.	0.861	0.873	0.853
% Corporate Citations	0.913	.	0.728	0.853	0.938
% Home-State Citations	0.845	.	0.868	0.875	0.838
% Corporate Inventor	0.832	.	0.702	0.841	0.884
% Home-State Inventor	0.854	.	0.863	0.849	0.852

Notes: Table reports summary statistics for our estimation sample. This includes all mainland US states, excluding Louisiana, from 1940-2000. Columns (1) and (2) report the mean and standard deviation, respectively, for the full sample period, while columns (3)-(5) report the averages in each 20-year period from 1940 to 2000. "State MTR" refers to the state's marginal tax rate excluding federal taxes, while "MTR" refers to tax rates inclusive of both federal and state tax liabilities. "Home-State Patents" are patents which are granted to inventors who live in the state in which they first appear in the data. Additional summary statistics, including those regarding logged outcome variables, corporate tax base rules, other outcome variables and control variables are included in Appendix Table A2. Inventors are included between the years of their first successful patent application and their last successful patent application. Inventor-level summary statistics are averaged over inventor-year observations to reflect summary statistics of our estimation sample. More summary statistics are in Appendix A.3.

Table 2: Macro Effects of Taxation

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
PANEL A: OLS				
$\ln(1-MTR90)$	1.803***	1.516***	1.784***	0.056
	(0.450)	(0.507)	(0.427)	(0.071)
ln(1− Corp. MTR)	2.759***	2.382***	2.308***	0.573***
	(0.701)	(0.770)	(0.640)	(0.141)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14
PANEL B: OLS CONTROLLING FOR CORPORATE TAX BASE				
$\ln(1-MTR90)$	1.967***	1.628***	1.896***	0.195***
	(0.391)	(0.466)	(0.383)	(0.058)
ln(1− Corp. MTR)	2.376***	2.307***	2.051***	0.341**
	(0.733)	(0.830)	(0.681)	(0.128)
Tax Base Index	0.173**	0.196**	0.216***	0.023*
	(0.082)	(0.094)	(0.078)	(0.012)
Base Index × ln(1− Corp MTR)	0.220*	0.198	0.279**	0.026
	(0.124)	(0.140)	(0.119)	(0.018)
Observations	2256	2256	2256	2256
Mean of Dep. Var.	7.17	9.86	7.24	0.76
S.D. of Dep. Var.	1.28	1.52	1.29	0.11
PANEL C: IV				
$\ln(1-MTR90)$	2.294**	1.976*	2.281**	-0.173
	(0.956)	(1.083)	(0.893)	(0.150)
ln(1− Corp. MTR)	3.540***	2.793***	3.015***	0.665***
	(0.943)	(1.047)	(0.866)	(0.208)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: Table reports estimates from a regression following equation (3). Robust standard errors two-way clustered at state × five-year and year level in parentheses. All regressions control for lagged population density, real personal income per capita, R&D tax credits, state and year fixed effects and are weighted by state population in 1940. Tax rates are lagged by 3-years and measured as log net-of-tax rates. Panel A shows OLS estimates. Panel B shows IV estimates, where personal tax rates and corporate tax rates are instrumented for by the predicted tax rates from (6) and (8) respectively. Panel C reports OLS estimates which additionally control for a corporate tax base index, constructed as in Suárez Serrato and Zidar (2018) by taking the predicted value from a regression of state-level corporate tax revenues on a variety of corporate tax base and apportionment rules. Mainland states, excluding Louisiana, included for the period 1940-2000. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table 3: State-level Long-Difference specifications

	Δ Log Patents (1)	Δ Log Citations (2)	Δ Log Inventors (3)	Δ Share Assigned (4)
PANEL A: 20-YEAR LONG DIFFERENCE				
$\Delta \ln(1 - MTR90)$	1.452***	1.099***	1.472***	0.096*
	(0.117)	(0.165)	(0.126)	(0.050)
$\Delta \ln(1-$ Corp. MTR)	1.980***	1.877***	1.752***	0.442***
	(0.243)	(0.277)	(0.230)	(0.082)
Observations	1927	1927	1927	1927
Mean of Dep. Var.	0.29	0.81	0.44	0.09
S.D. of Dep. Var.	0.48	0.67	0.45	0.12
PANEL B: 15-YEAR LONG DIFFERENCE				
$\Delta \ln(1 - MTR90)$	1.090***	0.729***	1.168***	0.055
	(0.080)	(0.130)	(0.083)	(0.044)
$\Delta \ln(1-$ Corp. MTR)	1.511***	1.216***	1.325***	0.313***
	(0.250)	(0.298)	(0.247)	(0.062)
Observations	2162	2162	2162	2162
Mean of Dep. Var.	0.26	0.66	0.37	0.07
S.D. of Dep. Var.	0.46	0.64	0.44	0.10
PANEL C: 10-YEAR LONG DIFFERENCE				
$\Delta \ln(1 - MTR90)$	0.780***	0.563***	0.849***	0.068**
	(0.146)	(0.152)	(0.155)	(0.028)
$\Delta \ln(1-$ Corp. MTR)	1.317***	0.972**	1.242***	0.163*
	(0.306)	(0.391)	(0.325)	(0.090)
Observations	2397	2397	2397	2397
Mean of Dep. Var.	0.20	0.46	0.27	0.05
S.D. of Dep. Var.	0.37	0.54	0.36	0.09

Notes: Table reports estimates from state-level long-difference specifications following equation (4). Panel A considers 20-year long differences, Panel B considers 15-year long differences, while Panel C considers 10-year long differences. Standard errors two-way clustered at state × five-year and year level are reported in parentheses. All regressions include controls for long-differences in personal income/capita, R&D tax credits, population density, and corporate tax base index, as well as year fixed effects. Regressions are weighted by 1940 state population.

Table 4: Effects of Taxes at the Individual Inventor Level

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.478***	0.423***	0.817***	1.149***	0.259***
	(0.067)	(0.065)	(0.164)	(0.171)	(0.093)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.421	0.518	0.580	0.717	0.809
ln(1− Personal MTR)	0.432***	0.380***	0.764***	1.026***	0.277***
	(0.056)	(0.058)	(0.145)	(0.149)	(0.084)
ln(1− Corp. MTR)	0.074	0.073	0.095	0.119	0.002
	(0.063)	(0.063)	(0.113)	(0.216)	(0.109)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.420	0.517	0.578	0.717	0.807

Notes: Table reports coefficients estimated from OLS regressions at the individual inventor level. Standard errors two-way clustered at state and year level reported in parentheses. Inventors are included in the sample between the years they first apply for a patent and the year of their final patent application. Mainland states, excluding Louisiana, included for the period 1940-2000. Personal MTR is defined as the marginal tax rate faced by the 90^{th} percentile earner in state s in year t for high productivity inventors, and the marginal tax rate rate faced by the median earner for low productivity inventors. High productivity inventors defined to be those who are in the top 10% of the national distribution of cumulative patents among active inventors. See Section 5.1 for details. Tax rates are lagged by 3-years and measured as log net-of-tax rates. Regressions with state and year fixed effects include controls for one-year lagged real state personal income per capita and population density, and R&D tax credits lagged by three years. All regressions include controls for inventor productivity, a quadratic in inventor tenure, and a local agglomeration force, measured as the number of patents applied for in the inventor's modal class in state s in year $t-1$ by other residents of the state. All dependent variables aggregate over three years: between period t and $t+2$. The dependent variables are: (1) an indicator for whether the inventor has a patent, (2) an indicator for whether the inventor has at least 10 citations, (3) the natural log of patents, (4) the natural log of citations received, and (5) an indicator for whether an individual has patents with above-median Kogan et al. (2017) patent value. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 5: Inventors' Location Choices: Multinomial Logit Estimations

	(1)	(2)	(3)	(4)
$\ln(1 - ATR^{pj[i]})$	1.104^{*}	1.366^{**}	1.498^{**}	2.306^{***}
	(0.594)	(0.590)	(0.586)	(0.735)
ln(1− Corp. MTR)	3.310^{***}			
	(0.557)			
Agglomeration Forces	0.184^{***}	0.255^{***}	0.213^{***}	0.206^{***}
	(0.029)	(0.045)	(0.050)	(0.040)
Home State Flag	3.815^{***}	3.794^{***}	3.793^{***}	3.610^{***}
	(0.017)	(0.018)	(0.018)	(0.017)
Interaction coefficients:				
Agglomeration			-0.273^{**}	
			(0.115)	
Assignee Has Patent				-1.801^{***}
				(0.356)
Fixed Effects	State + Year	State × Year	State × Year	State × Year
Baseline Pers. Tax Elasticity	0.340	0.322	0.353	0.465
	(0.183)	(0.139)	(0.138)	(0.148)
Pers. Tax Elasticity: Home State	0.135	0.102	0.111	0.150
	(0.073)	(0.044)	(0.044)	(0.048)
Pers. Tax Elasticity: Non-Home State	0.979	1.050	1.151	1.502
	(0.526)	(0.454)	(0.450)	(0.479)
Corp. Tax Elasticity	1.019			
	(0.172)			
Corp. Tax Elasticity: Home State	0.405			
	(0.068)			
Corp. Tax Elasticity: Non-Home State	2.934			
	(0.494)			
Observations	4197104	2002776	2002776	2002776

Notes: Table reports coefficients estimated from the multinomial logistic regression specified in Section 5.4. $ATR^{pj[i]}$ represents the average personal tax rate faced by an individual i who is at the j^{th} income percentile locating in a given state and year. We assign tax rates to inventors following the procedure laid out in Section 5.4. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All tax rates are lagged by one year and included as log net-of-tax rates. All specifications include controls for a quadratic in inventor tenure which is allowed to vary by destination state, as well as home state × high productivity fixed effects. The regression with state + year fixed effects (column 1) additionally controls for one-year lags of state personal income per capita, population density, R&D tax credits and our index of corporate tax base breadth. For the sake of computational feasibility, we restrict attention to the eight states which are both among the fifteen most inventive states by total patent counts and ever have a progressive tax spell (i.e. charge a different marginal tax rate to 90^{th} percentile and median earners). This sample restriction yields possible choice states of California, Maryland, Massachusetts, Minnesota, New Jersey, New York, Ohio, and Wisconsin. Inventors are only included in the years in which they have at least one patent. Local agglomeration forces are proxied by the number of patents applied for in the inventor's modal class in state s in year t by other residents in the state, divided by 1,000. The rows under "*Interaction coefficients:*" report the coefficients on an interaction of $\ln(1 - ATR^{pj[i]})$ with the variable in question. "Baseline Pers. tax Elasticity" reports the elasticity implied by the coefficient on the uninteracted $\ln(1 - ATR^{pj[i]})$, calculated following Kleven et al. (2013) and described in Appendix A.2. $^{*}p < 0.1$,$^{**}p < 0.05$,$^{***}p < 0.01$.

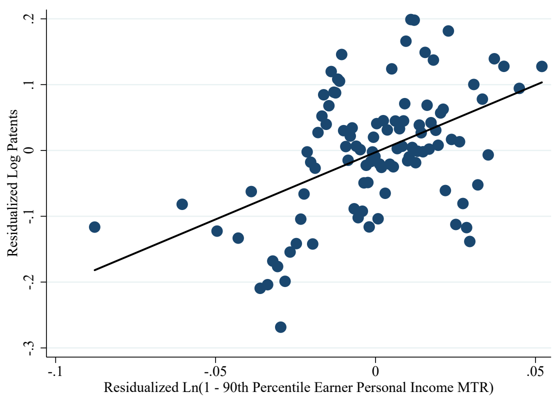
Table 6: Corporate vs Non-Corporate Inventor Elasticities

	Corporate Inventors		Non-Corporate Inventors	
Tax Type:	Personal	Corporate	Personal	Corporate
	(1)	(2)	(3)	(4)
# Patents	1.09***	0.49**	4.14***	-0.76
	(0.27)	(0.21)	(1.15)	(0.89)
Has Citation	0.00	0.10***	0.45***	-0.04
	(0.03)	(0.03)	(0.10)	(0.09)
# Citations, conditional > 0	0.94***	0.36*	1.42***	-0.71***
	(0.14)	(0.20)	(0.24)	(0.24)
Mobility	0.20	1.25***	0.72**	0.60***
	(0.20)	(0.20)	(0.30)	(0.20)

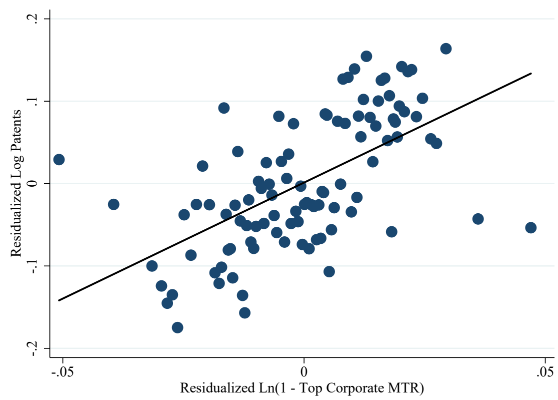
Notes: This table the estimated elasticity of various outcomes to the net-of-personal-tax rate (columns 1 and 3) and net-of-corporate-tax rate (columns 2 and 4). Columns 1 and 2 report the elasticities for corporate inventors, while columns 3 and 4 report them for non-corporate inventors. Corporate inventors are defined to be those who have at least one patent assigned to a corporation in the next three years. The first three rows report results from regression equation (15), estimated with OLS. These regressions contain inventor, state and year fixed effects, controls for whether the inventor is a corporate inventor, the tax base index split into bins of width 0.5, the tax base index bins interacted with the corporate inventor flag, a high quality flag interacted with a corporate inventor flag, and all the controls from Table 4. Inventors are included in these regressions for all years between their first and final successful (i.e. eventually granted) patent application. Standard errors two-way clustered at the state and year level reported in parentheses. The first two rows report elasticities defined as the estimated semi-elasticity from this regression divided by the group-specific mean of the dependent variable. In the text, we report the elasticity of citations to taxes, which we calculate by summing the elasticities for "Has Citation" and "# Citations, conditional > 0" (the second and third rows). Mobility elasticities by estimating multinomial logistic regressions following equation (14) and following the procedure of Kleven et al. (2013) and described in Appendix A.2. These multinomial regressions are estimated analogously to column 1 of Table 5 and include state plus year fixed effects and all the same control variables. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Figure 1: Binned Scatters

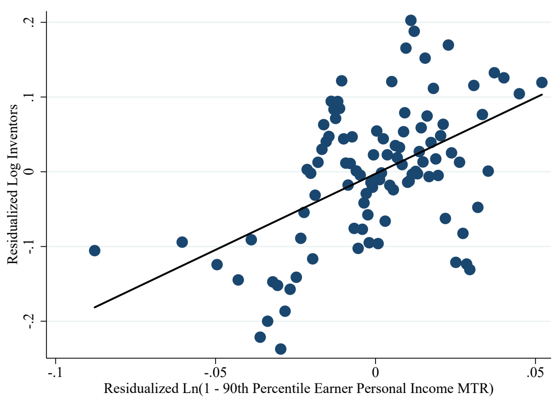
Panel A: 90^{th} percentile personal MTR on Log Patents



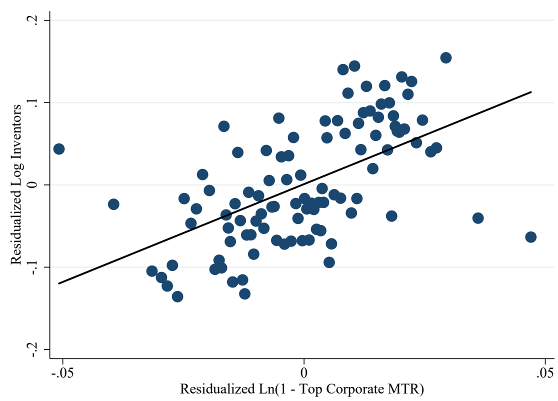
Panel B: Top Corporate MTR MTR on Log Patents



Panel C: 90^{th} percentile personal MTR on Log Inventors



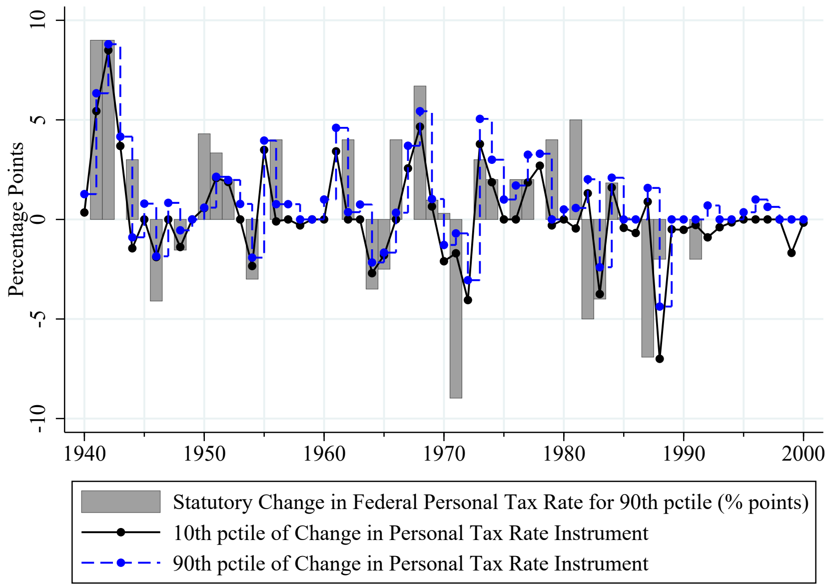
Panel D: Top Corporate MTR on Log Inventors



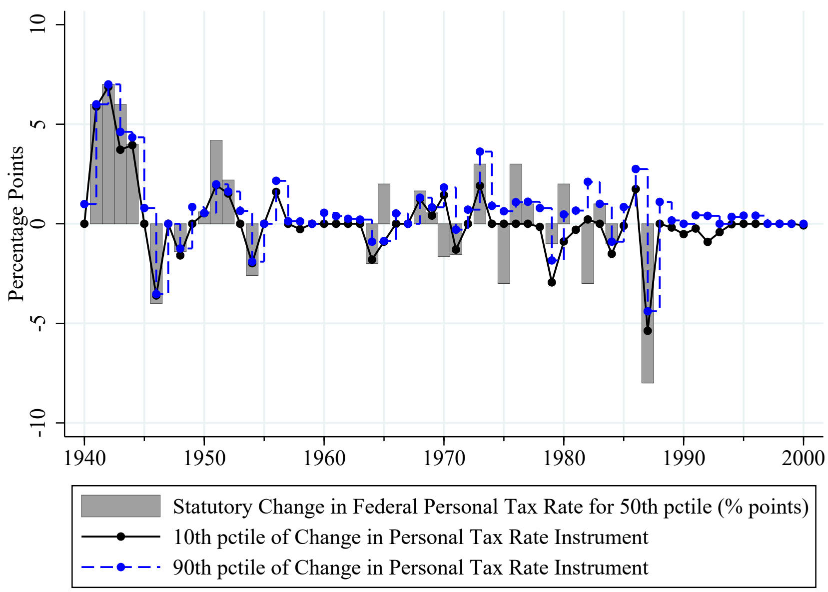
Notes: Figure plots binned scatter plots of effect of taxes at state level. The top row shows the effect on log patents, while the bottom row shows log inventors. The leftmost column shows the relationship between innovation and the marginal tax rates (MTRs) for the 90th percentile earners, and the rightmost column show effect of top corporate MTRs. All tax rates include both federal and state taxes. Both the horizontal and vertical axes are residualized against state and year fixed effects, as well as lagged population density, personal income per capita, and R&D tax credits. Panels A and C additionally residualize against the lagged corporate tax rate, while Panels B and D residualize against 90^{th} percentile personal income MTR. All mainland US states except Louisiana included over the period 1940–2000.

Figure 2: Visualizing IV Variation

Panel A: Personal Income Tax Rate for 90^{th} percentile earner



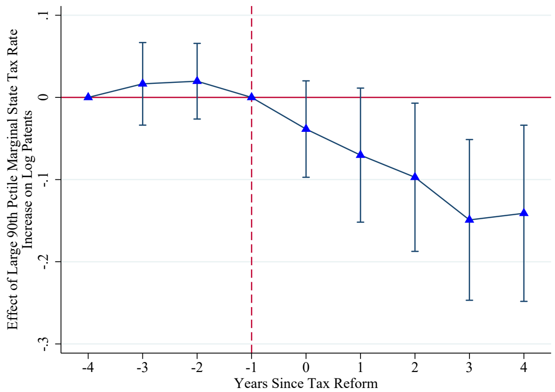
Panel B: Personal Income Tax Rate for median earner



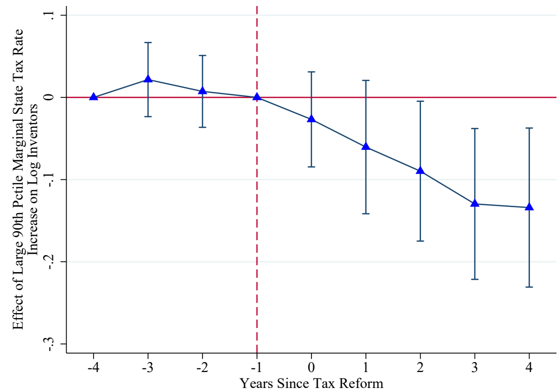
Notes: Figure plots the variation in our personal income tax instrument induced by federal tax changes. The gray bars plot the time series of changes in the statutory federal personal tax rate for a particular point in the earnings distribution: the 90th percentile in Panel A and the 50th percentile in Panel B. The dashed lines plot the distribution of induced changes in combined state and federal tax liabilities assuming that the state tax law were fixed to be the same as five years prior. The blue squares connected by dashed lines plot the 90th percentile of induced tax changes, while the black circles connected by solid lines plot the 10th percentile of induced tax changes. The income distribution is lagged by 5 years to produce this plot. That is, the blue and black lines plot the distribution of changes in the instrument for state personal taxes. Personal tax rates are instrumented for by the predicted tax rates given by equations (6).

Figure 3: State-Level Event Studies around Large Tax Reforms

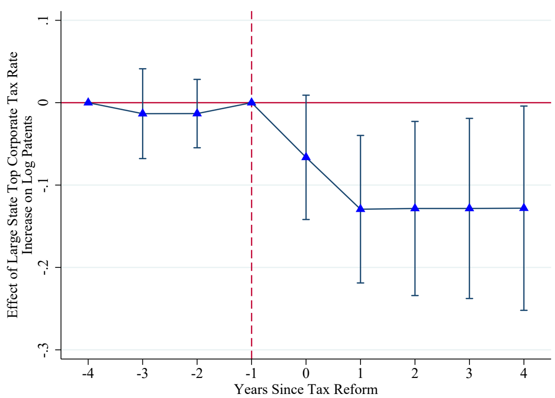
Panel A: 90^{th} percentile personal MTR on Log Patents



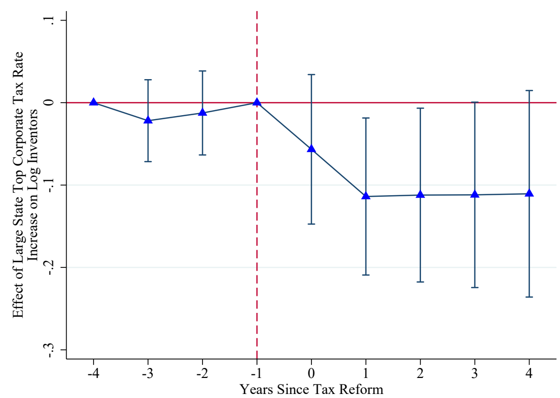
Panel B: 90^{th} percentile personal MTR on Log Inventors



Panel C: Top Corporate MTR on Log Patents



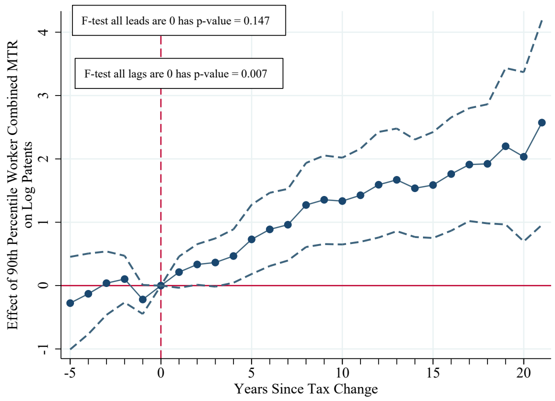
Panel D: Top Corporate MTR on Log Inventors



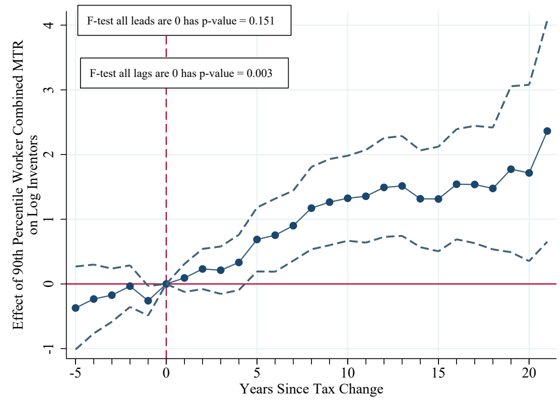
Notes: Figure reports estimates of γ_l from Equation (9), based on event study regressions around large tax reforms. A large tax reform is defined as being in the top 10% of state tax changes in the period 1940-2000 that does not have another large reform within 4 years before or after the focal reform. Panels A and B consider state tax reforms affecting the personal tax rate for the 90^{th} percentile earner, while Panels C and D consider large reforms to the top statutory corporate tax rate. We generate a synthetic control state for each reform following Abadie et al. (2010) by matching on pre-reform outcomes (patents or inventors), population density, and personal income/capita averaged over the 4 years prior to the reform. Only states that do not themselves have a large reform in the event window are eligible to be included in the synthetic control. See Section 4.3 for details. All regressions include reform $\times$ treatment state fixed effects and relative year fixed effects and are unweighted. Bars represent 95% confidence intervals using standard errors clustered at the reform level.

Figure 4: State-Level Distributed Lag Regressions

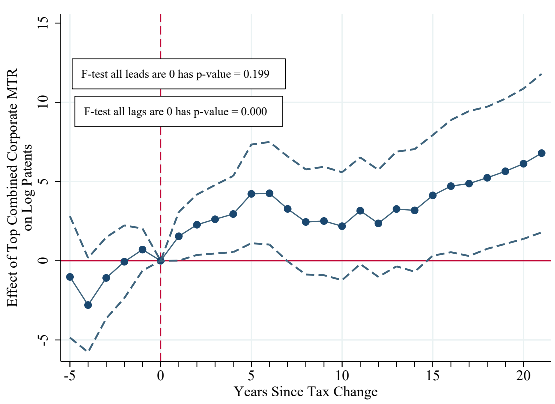
Panel A: 90^{th} percentile personal MTR on Log Patents



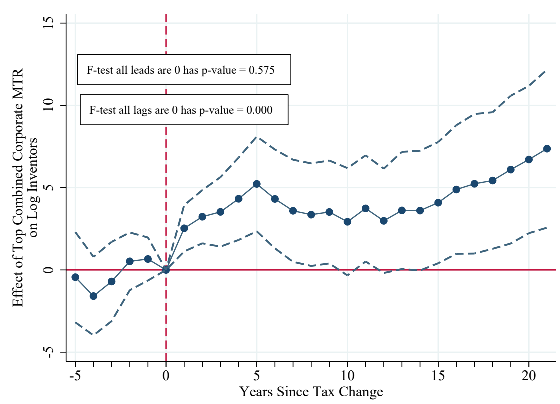
Panel B: 90^{th} percentile personal MTR on Log Inventors



Panel C: Top Corporate on Log Patents



Panel D: Top Corporate MTR on Log Inventors



Notes: Figure reports estimates from the distributed lag model described in equation (10). Specifically, we plot $\mathcal{B}_l$, which represents the cumulative effect of a one unit change in the log net-of-tax-rate in year t through year $t + l$, normalizing the value of the zero-lag change to 0. Coefficients may thus be interpreted as cumulative elasticities. See Section 4.4 for details. All regressions include 1-year lagged controls for personal income/capita, population density and R&D tax credits, all included as one-year changes, as well as year fixed effects, and are weighted by each state's 1940 population count. Corporate tax regressions additional include controls for the distributed lag of individual corporate tax base rules, namely whether the state has a sales apportionment weight, the sales and payroll apportionment weights, and the number of years that losses are allowed to be carried forward or back. Regressions focusing on personal income taxes additionally control for three-year lagged one-year changes in corporate income taxes and vice versa. All taxes include both state and federal tax liabilities. Dashed lines indicate 90% confidence intervals calculated using standard errors clustered at the state level.

APPENDIX

A.1 Variable Definitions

In this section, we detail the construction of relevant variables for our analysis. Variables related to corporate tax base rules are described in detail in Section OA.2.

- *Top Corporate Marginal Tax Rate (Corp. MTR)* - The additional tax burden accruing to a firm in the top tax bracket in state s for an additional one dollar of revenue if all of its operations were in s.

- *90th Percentile Income Marginal Tax Rate (MTR90)* - The additional tax burden accruing to an individual at the 90th percentile of the national income distribution for an additional one dollar of earnings. Calculated using the tax calculator by Bakija (2017).

- *90th Percentile Income Average Tax Rate (ATR90)* - The total tax burden for an individual at the 90th percentile of the national income distribution divided by that individual's total income. Calculated using the tax calculator by Bakija (2017).

- *Median Income Marginal Tax Rate (MTR50)* - The additional tax burden accruing to an individual at the 50th percentile of the national income distribution for an additional one dollar of earnings. Calculated using the tax calculator by Bakija (2017). Data on median incomes come from the Census. Table P-53 reports the median income for men back to 1947. These data are available from `https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-income-people.html`. We also use income data from the 1940 decennial Census, and log-linearly interpolate median incomes from 1940 through 1947.

- *Median Income Average Tax Rate (ATR50)* - The total tax burden for an individual at the 50th percentile of the national income distribution divided by that individual's total income. Calculated using the tax calculator by Bakija (2017).

- *Inventor productivity* - An inventor's productivity in year t is defined to be the number of eventually-granted patents that the inventor has applied for as of year $t-1$. In robustness table A29, inventor i's productivity in year t is defined to be the total number of citations ever received by patents applied for by i through year t. An inventor is said to be "high productivity" in year t if they are in the top 10% of the national inventor productivity distribution in year t. In robustness table A26, an inventor is said to be high productivity if they are in the top 5% of the national productivity distribution in year t. Finally, robustness table A28 allows an inventor to be high productivity if they are in the top 10% of the productivity distribution, of middle productivity if they are between the 75th and 90th percentile of the productivity distribution, and low productivity otherwise.

- *Personal MTR* - An inventor's effective marginal (average) tax rate is defined to be the marginal (average) tax rate faced by the 90^{th} percentile earner in the national income distribution if the inventor is high productivity, and the marginal (average) tax rate faced by a median earner if the inventor is low productivity. In appendix table A28, middle productivity inventors have an effective tax rate equal to the tax rate faced by an individual earning at the 75^{th} percentile of the national income distribution. In all regressions, we use lagged effective tax rates as independent variables. Thus an inventor living in state s will face an effective tax rate for innovation output in year t which is the effective tax rate the inventor would have faced in year $t-1$ given their $t-1$ productivity level and the tax laws in place in year $t-1$.

- *Log Patents* - The natural logarithm of the number of eventually-granted patents applied for in state s in year t. In inventor-level regressions, this variable corresponds to the log of the number of eventually-granted patents applied for by inventor i in years t through $t+2$.

- *Log Citations* - The natural logarithm of the number of citations ever received by eventually-granted patents which were applied for in state s in year t. In inventor-level regressions, this variable corresponds to the log of the number of citations ever received by eventually-granted patents which were applied for by inventor i in years t through $t+2$. Citation counts adjusted according to the algorithm of Hall et al. (2001), detailed for our data in Appendix OA.4.

- *Log Inventors* - The natural logarithm of number of inventors in state s in year t as implied by the Lai et al. (2014) algorithm applied to our dataset. A detailed description of this algorithm is provided in Appendix OA.1.

- *Corporate Patent* - A corporate patent is one which is assigned to a corporation after being granted.

- *Share Assigned* - The share of patents in state s in year t which are assigned to a corporation.

- *Has Patent* - An indicator variable, equal to 1 if the inventor has at least one successful patent application between years t and $t+2$. Inventors are included in the regression sample for the period between their first ever successful patent application, and their last ever successful patent application.

- *Has 10+ Cites* - An indicator variable, equal to 1 if the inventor's patents, applied for between years t and $t+2$, ever receive at least 10 citations in total between them. Inventors are included in the regression sample for the period between their first ever successful patent application, and their last ever successful patent application. Patent citation counts adjusted according to the algorithm of Hall et al. (2001), detailed for our data in Appendix OA.4.

- *Corporate Inventor* - An inventor is said to be a corporate inventor in year t if they are granted at least one corporate patent in the next three years.

- *Agglomeration* - The number of patents, in thousands, applied for by inventors $j \neq i$ who share inventor i's modal patent class in year t in state s.
- *Home State Flag* - An indicator variable equal to one if the state is the first state in which the inventor applies for a patent.
- *Assignee Has Patent* - An indicator variable equal to one if an inventor i's firm has at least one patent applied for in year t by an inventor $j \neq i$ in destination state s.
- *Inventor Tenure/Experience* - an inventor's tenure is the number of years that have passed since the inventor's first successful patent application.
- *Personal Income per Capita* - state level personal income per capita, included in regressions in units of tens of thousands of 1982 dollars. Downloaded from `https://www.bea.gov/data/economic-accounts/regional`, accessed on March 15, 2021.
- *R&D Tax Credit:* statutory credit rate adjusted for recapture and type of credit for a given state-year;
- *Population Density* - thousands of people per square kilometer.
- *Tax Base Index* - corporate tax base index. Higher values generally correspond to broader tax bases. Construction of the index is detailed in Appendix OA.2.
- *State Governor: Democrat* - an indicator variable equal to 1 if the state's governor is a Democrat.
- *% State Upper House Democrat* - the percent of a state's Upper House of the legislative branch who is a Democrat.
- *% State Lower House Democrat* - the percent of a state's Lower House of the legislative branch who is a Democrat.
- *State Pat./State Patents* - the natural log of the total number of patents applied for in the inventor's residence state.
- *Kogan et al. (2017) patent value* - Patent value constructed by Kogan et al. (2017) by considering jumps in the total stock market value of an assignee in a short window around the successful patent grant, deflated to millions of 1982 dollars. This is only defined for patents granted to publicly-traded corporations.
- *Has High-Value Patent (Pat.)* - An indicator variable equal to one if an inventor has, over the subsequent three years, Kogan et al. (2017) stock market value of patents applied for among all corporate inventors active in year t.

A.2 Calculating Multinomial Logit Elasticities

The elasticity of an inventor i residing in state s to the personal tax rate may be expressed as[36]

$$\eta_{st}^{i} = \frac{d \ln P_{st}^{i}}{d \ln(1 - ATR_{st}^{pj[i]})} = \alpha \cdot (1 - P_{st}^{i})$$

We may then define the elasticity of location choices to tax rates by taking the weighted average of these η_{st}^{i}. We may do this separately inventors' home state and non-home states. Letting I_s^d and I_s^o denote home and non-home inventors in state s, the elasticity of locating in state s to personal taxes may be expressed as

$$\eta_p^{s,d} \equiv \frac{d \log \sum_{i \in I_s^d} P_{st}^{i}}{d \ln(1 - ATR_{st})} = \frac{\alpha \sum_{i \in I^d} P_{st}^{i}(1 - P_{st}^{i})}{\sum_{i \in I_s^d} P_{st}^{i}}. \tag{A1}$$

Likewise, for inventors in non-home states,

$$\eta_p^{s,d} \equiv \frac{d \log \sum_{i \in I_s^o} P_{st}^{i}}{d \ln(1 - ATR_{st})} = \frac{\alpha \sum_{i \in I^o} P_{st}^{i}(1 - P_{st}^{i})}{\sum_{i \in I_s^d = o} P_{st}^{i}}. \tag{A2}$$

Average home and non-home elasticities are then defined as the weighted average of these elasticities across all countries:

$$\eta_p^d \equiv \sum_s \left(\frac{\sum_{i \in I_t^d} P_{st}^{i}}{\sum_s \sum_{i \in I_t^d} P_{st}^{i}} \right) \eta_p^{s,d}, \tag{A3}$$

and

$$\eta_p^o \equiv \sum_s \left(\frac{\sum_{i \in I_t^o} P_{st}^{i}}{\sum_s \sum_{i \in I_t^o} P_{st}^{i}} \right) \eta_p^{s,o}, \tag{A4}$$

where I_t^d and I_t^o represent the set of inventors locating in their home state or out-of-state, as in Section 2. Finally, we may aggregate these elasticities to an overall mobility elasticity as

$$\eta_p \equiv \gamma^d \eta^d + (1 - \gamma^d) \eta^o. \tag{A5}$$

[36]Elasticities to the corporate tax may be defined analogously.

A.3 Additional Tables and Figures

A.1 Summary Statistics

Table A1: Disambiguation Output: Unique Inventor Counts

Sample	# Inventors	# Patents
1920-2004, US only	2,953,471	5,336,672
1940-2000, US only	1,744,224	2,775,100
Lai et al. Patents, our disambiguation	1,374,891	2,179,599
Lai et al. Disambig (US)	1,462,626	2,179,599

Notes: Table shows performance of the Lai et al. disambiguation algorithm as applied to our historical patent data. Each row contains performance information for a different subsample. The category "Lai et al. Patents, our disambiguation" reports the performance of our algorithm on the patent records included in the original Lai et al. sample. Likewise, "Lai et al. Disambig (US)" reports the number of unique inventors that Lai et al. find when applying their algorithm to U.S. patents. The first column shows the number of unique inventors found by the disambiguation algorithm, while the second shows the unique number of patents in each subsample.

Table A2: Additional Summary Statistics

	Mean (1)	S.D. (2)	1940-59 (3)	1960-79 (4)	1980-99 (5)
Inventor-Level Data: Controls/Other Outcomes					
Pr{Has corporate patent in 3 years}	0.564	0.496	0.437	0.566	0.619
Pr{Has non-corporate patent in 3 years}	0.165	0.371	0.244	0.154	0.136
Agglomeration forces	0.068	0.215	0.017	0.029	0.114
Tenure	9.726	13.245	9.380	9.942	9.745
Pr{Assignee has patents in multiple states}	0.790	0.407	0.797	0.794	0.784
State-Level Data: Other Outcomes					
Log Patents	5.96	1.51	5.54	5.98	6.35
Log Inventors	5.97	1.53	5.44	6.00	6.49
Log Citations	8.52	1.77	7.69	8.30	9.56
Mean Kogan et al. (2017) Patent Value	23.71	16.71	23.94	26.99	20.25
Real Manufacturing Value Added ($ billions)	5.08	6.40	2.67	5.56	7.02
Real Manufacturing Total Payrolls ($ billions)	2.30	2.93	1.43	2.73	2.74
Real Average Weekly Earnings	102.47	22.61	80.59	113.34	113.47
Employees per Establishment	51.10	20.21	50.21	53.97	49.13
Real Personal Income Per Capita ($ 0000s)	3.31	1.27	2.04	3.27	4.62
Share of Workforce in Manufacturing	0.22	0.12	0.29	0.23	0.15
State-Level Data: Corporate Tax Rules					
Share with Sales Apportionment Weight	0.95	0.22	0.83	0.97	1.00
Sales Apportionment Weight	42.27	23.50	39.44	37.90	47.33
Property Apportionment Weight	30.13	15.54	35.14	31.34	26.32
Payroll Apportionment Weight	25.62	13.39	19.95	28.69	26.32
Years Losses Allowed to be Carried Back	1.19	1.45	0.10	1.16	1.29
Years Losses Allowed to be Carried Forward	6.69	5.87	1.41	3.19	9.76

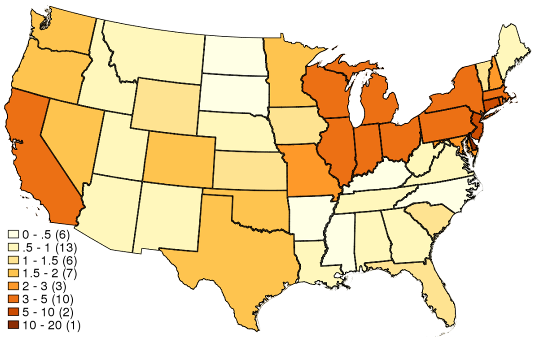
Notes: Table reports additional summary statistics for our estimation sample. This includes all mainland US states, excluding Louisiana, from 1940-2000. Columns (1) and (2) report the mean and standard deviation, respectively, for the full sample period, while columns (3)-(5) report the averages in each 20-year period from 1940 to 2000. “Tenure” corresponds to the number of years the inventor has been in the sample since her first patent. Inventors are included between the years of their first successful patent application and their last successful patent application. Summary statistics for all inventor controls are averaged over inventor-year observations to reflect summary statistics of our estimation sample; thus inventors with long careers will appear more than once in the average. Kogan et al. (2017) Patent Value is expressed in millions of 1982 dollars. Corporate tax base rules are defined in detail in Appendix OA.5, and are defined conditional on having non-zero state corporate tax rates.

Table A3: Summary Statistics on Inventor Careers

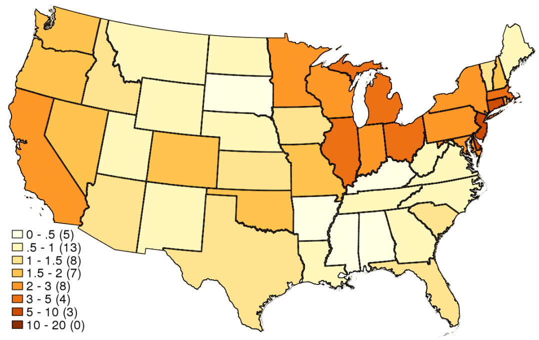
	Mean	Median	SD	90^{th}	95^{th}	99^{th}
Years Active	3.33	1.00	6.24	8.00	15.00	33.00
Number of States	1.07	1.00	0.38	1.00	2.00	3.00
Number of Patents	2.60	1.00	5.79	5.00	9.00	25.00
Patents Per Year	1.02	1.00	0.53	1.00	2.00	3.00
Total Citations Received	65.34	12.71	409.31	110.73	229.11	890.12
Citations Per Year	21.88	8.26	70.62	41.69	74.23	244.71
Number of Classes	1.62	1.00	1.75	3.00	4.00	9.00

Notes: Table reports summary statistics of our sample of disambiguated inventors. The categories "Number of States," "Number of Patents," "Total Citations Received," and "Number of Classes" refer to statistics over an inventor's entire career, while "Patents Per Year" and "Citations Per Year" refer to average numbers per year of an inventor's career. Each column reports a different moment of the distribution for the variable considered in the row. For instance, the 90^{th} percentile of the distribution of total career length ("Years Active") is 11 years, the 95^{th} percentile of that distribution is 19 years and the mean is 4.14 years. Inventors are considered active between the first year in which they have a successful patent application and the last year in which they have a successful patent application. All statistics are inventor-weighted, in contrast to Tables 1 and A2 which present statistics averaged over inventor $\times$ year observations. The table considers inventors active in our primary estimation sample: U.S. inventors between 1940 and 2000. The table therefore represents 1,744,224 inventors.

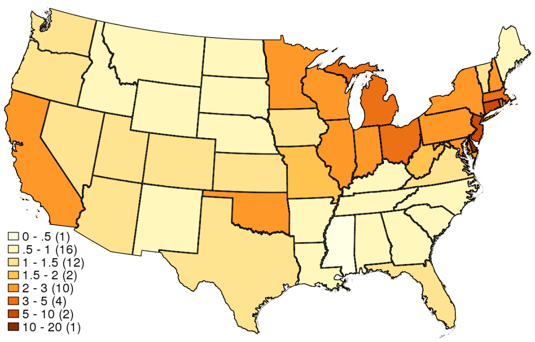
Figure A1: Patents per 10,000 State Residents Over Time



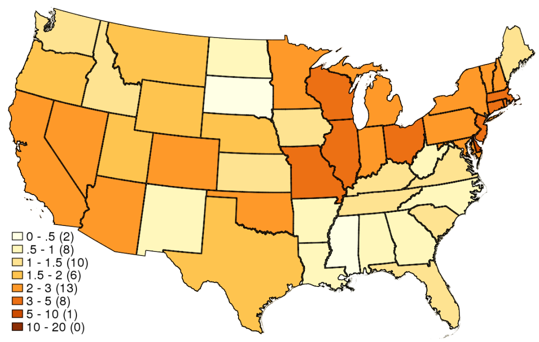
Panel A: 1940



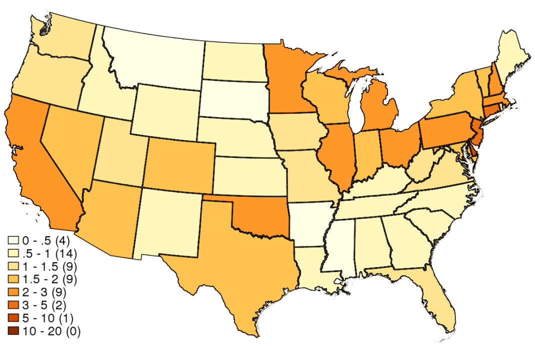
Panel B: 1950



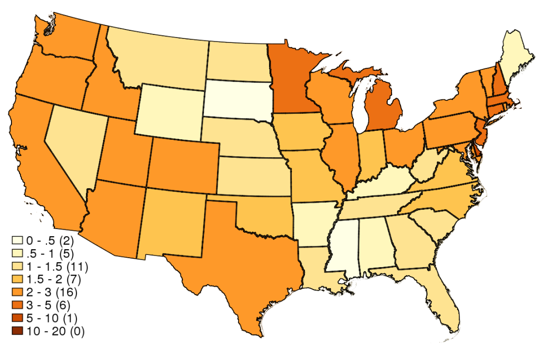
Panel C: 1960



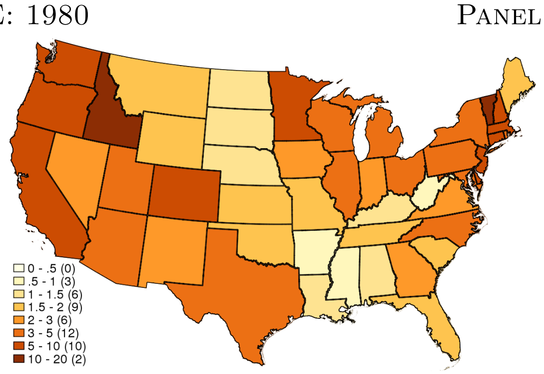
Panel D: 1970



Panel E: 1980



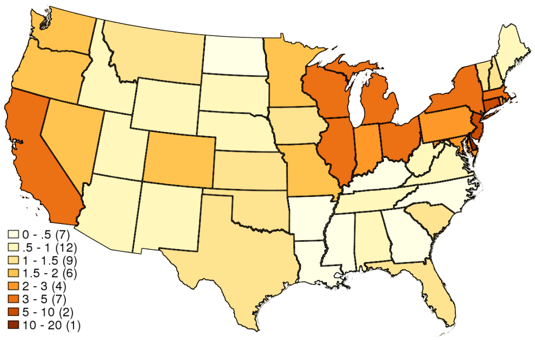
Panel F: 1990



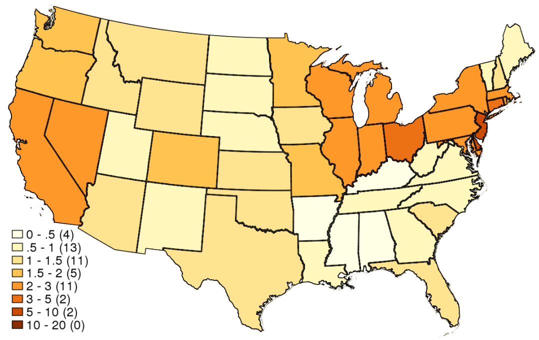
Panel G: 2000

Notes: Figure plots the number of patents per 10,000 state residences in each state every ten years from 1940 through 2000. Darker colors indicate more innovation.

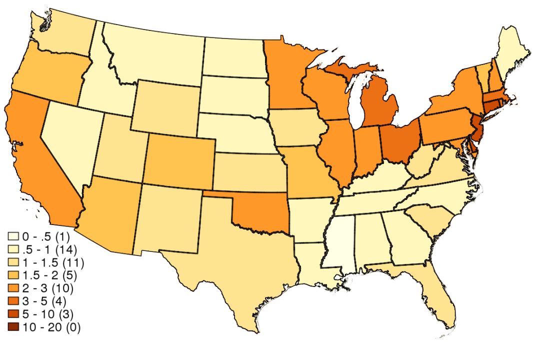
Figure A2: Inventors per 10,000 State Residents Over Time



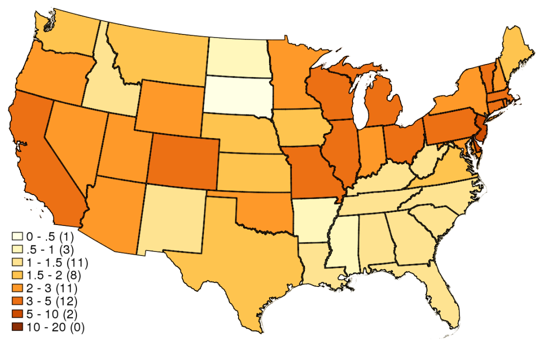
Panel A: 1940



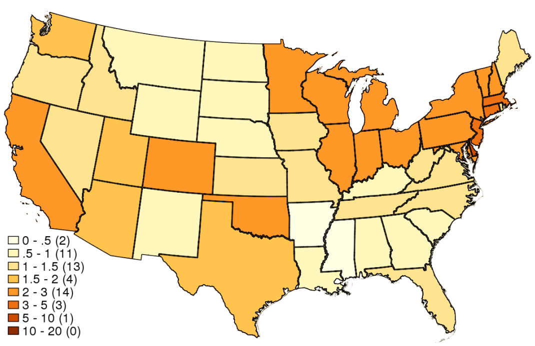
Panel B: 1950



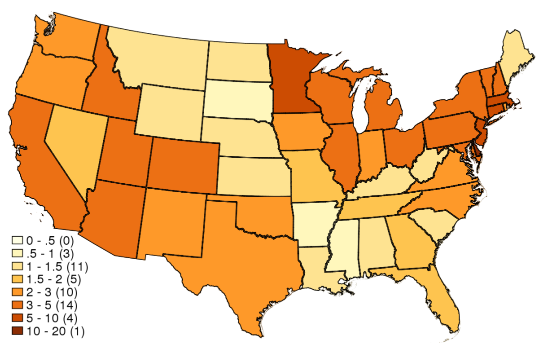
Panel C: 1960



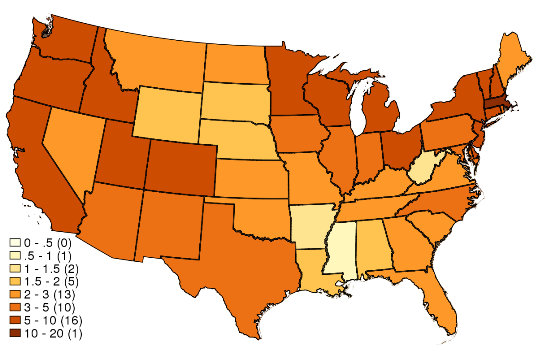
Panel D: 1970



Panel E: 1980



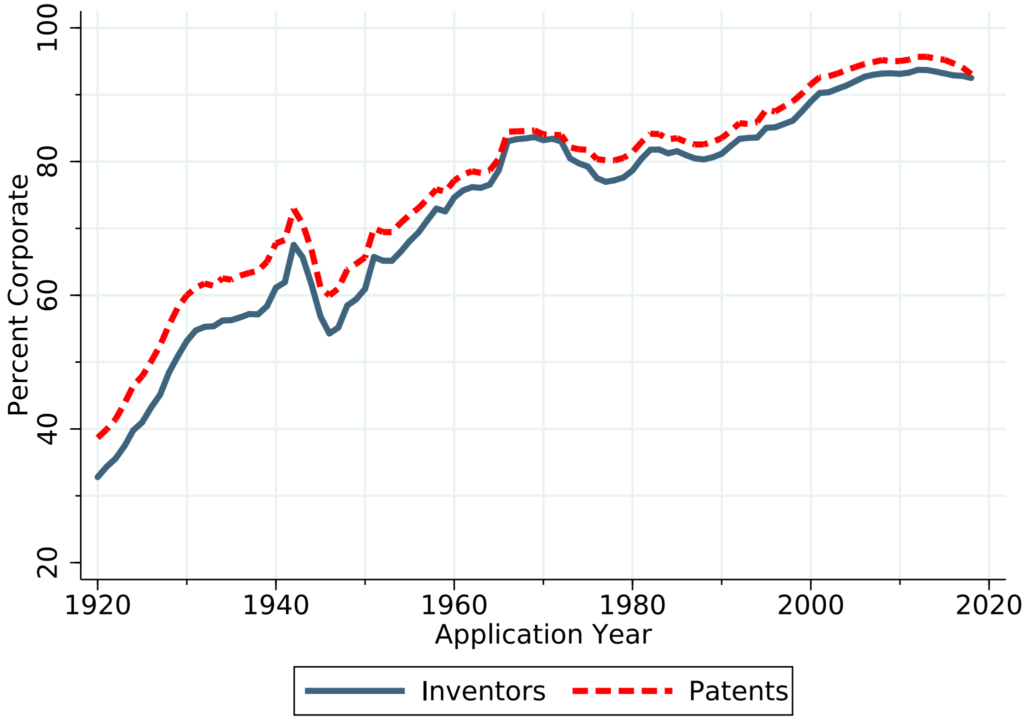
Panel F: 1990



Panel G: 2000

Notes: Figure plots the number of unique inventors per 10,000 state residences in each state every ten years from 1940 through 2000. Darker colors indicate more innovation.

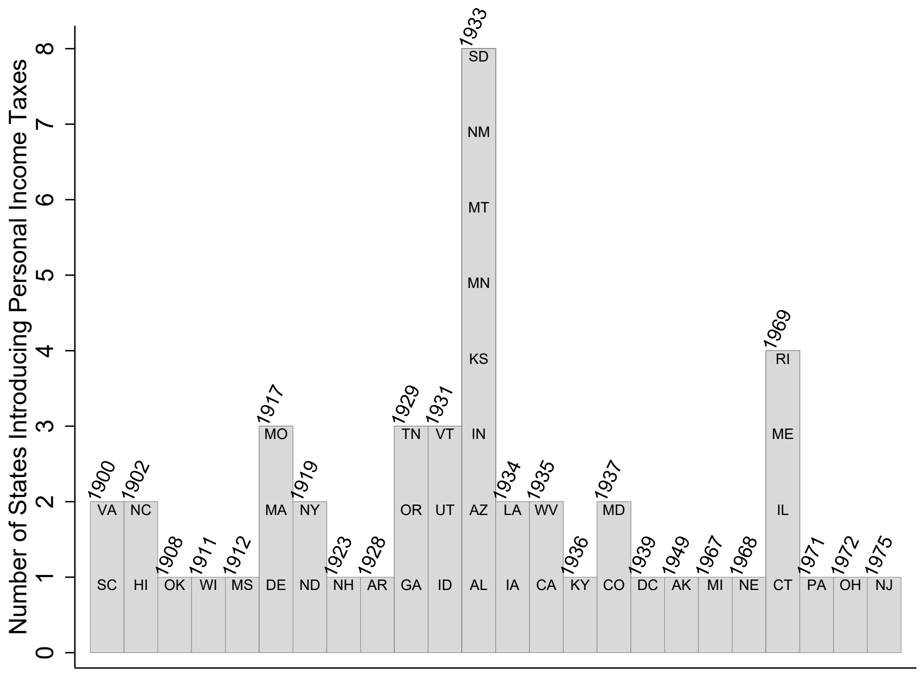
Figure A3: Share of Corporate Patents and Corporate Inventors



Notes: The graph shows the share of patents assigned to corporations (dashed line) and the share of inventors who patent for corporations (solid line).

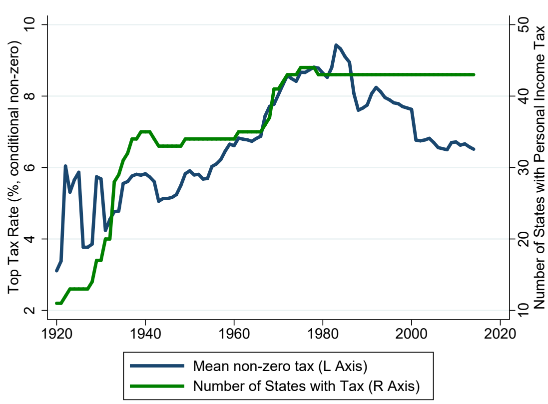
A.2 Summary of Tax Variation

Figure A4: Introduction Year of State Personal Income Taxes

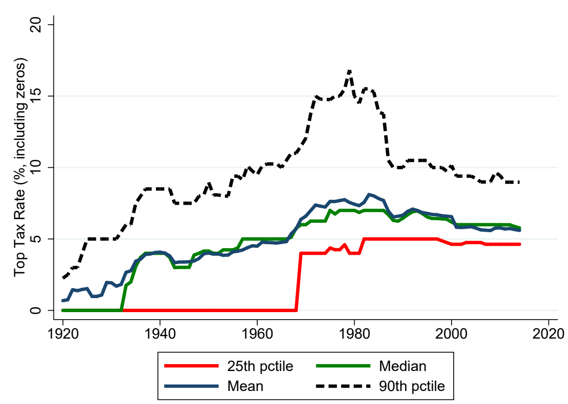


Notes: Figure plots the first year in which each state has a statutory personal income tax rate.

Figure A5: The Evolution of Personal Income Taxes



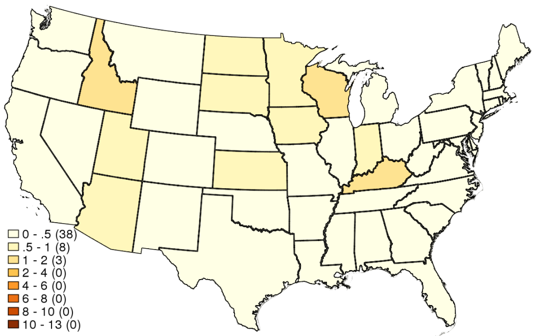
Panel A: Intensive and Extensive Margin



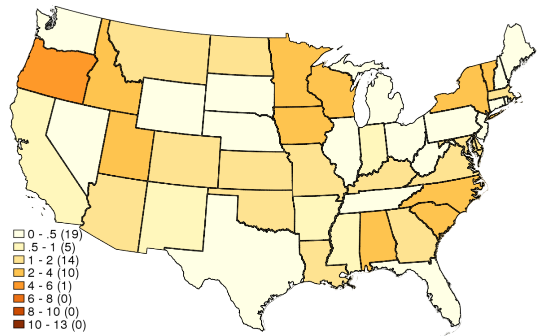
Panel B: Distribution of Statutory Tax Rates

Notes: Figure plots the share of states with a personal income tax, as well as the distribution of those taxes over time.

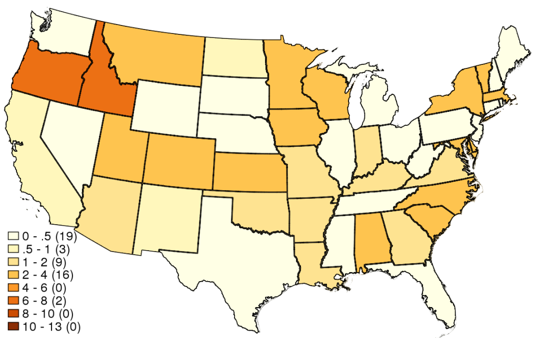
Figure A6: State Personal Marginal Tax Rates at the Median Income



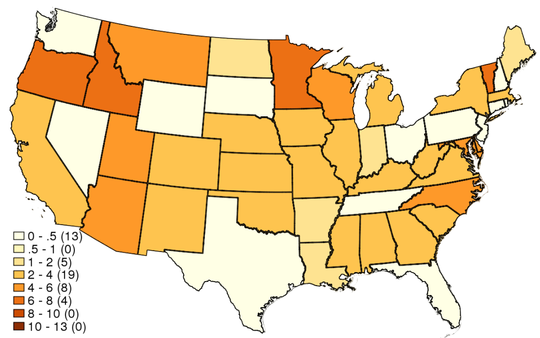
Panel A: 1940



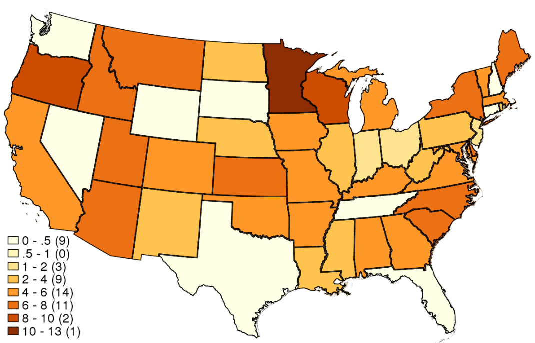
Panel B: 1950



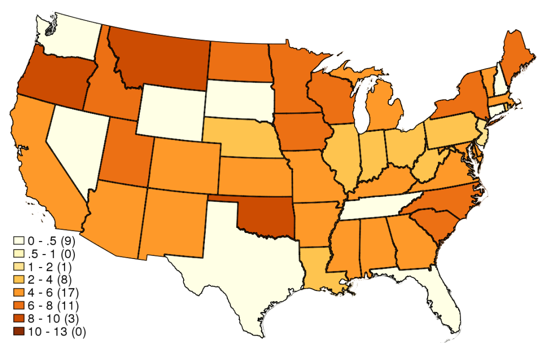
Panel C: 1960



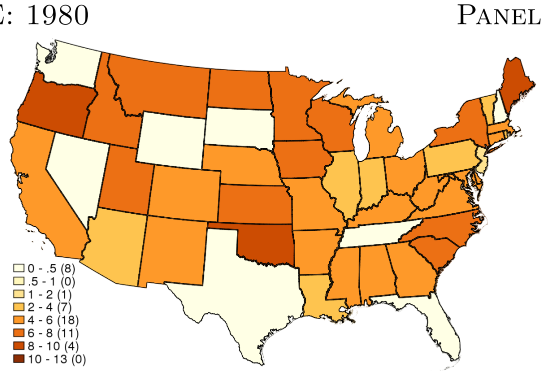
Panel D: 1970



Panel E: 1980



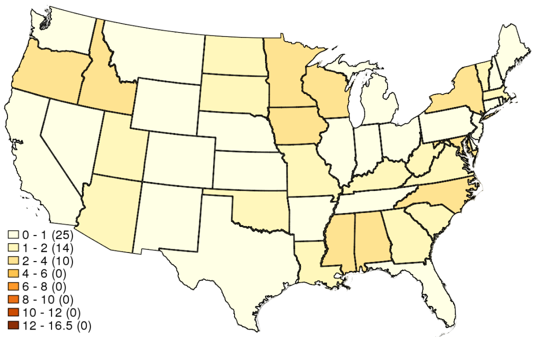
Panel F: 1990



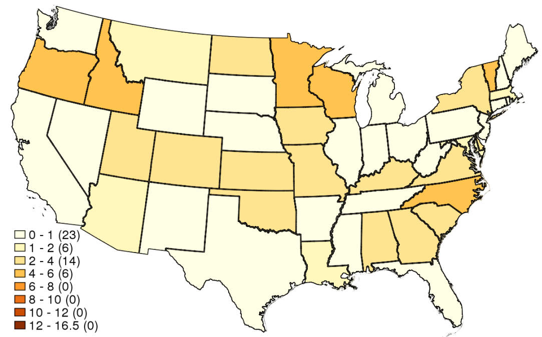
Panel G: 2000

Notes: Figure plots the state statutory marginal personal income tax rates faced by individuals whose adjusted gross income is equal to the median of the nation income distribution for men every ten years from 1940 through 2000. Darker colors indicate higher tax rates. Tax rates measured in percentage points.

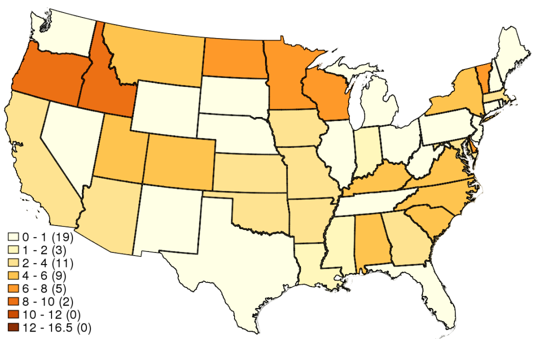
Figure A7: State Personal Marginal Tax Rates at 90th Income Percentile



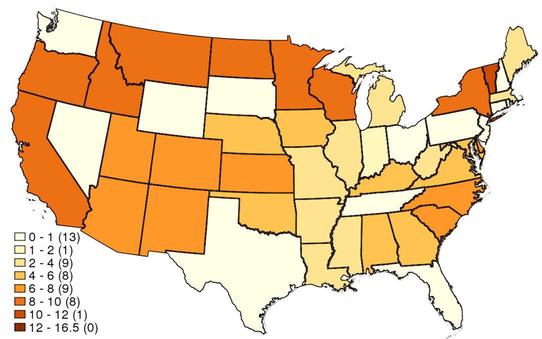
Panel A: 1940



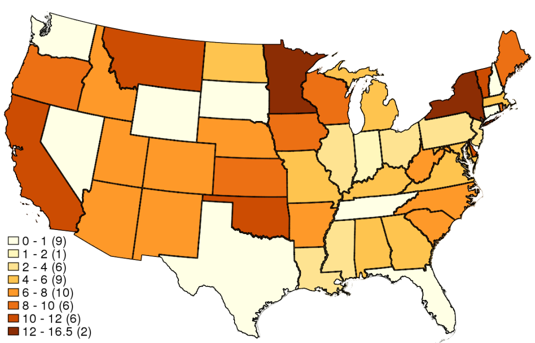
Panel B: 1950



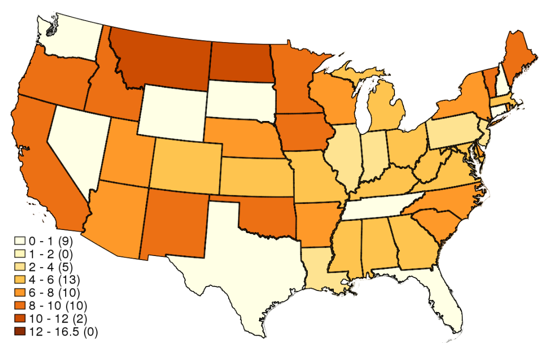
Panel C: 1960



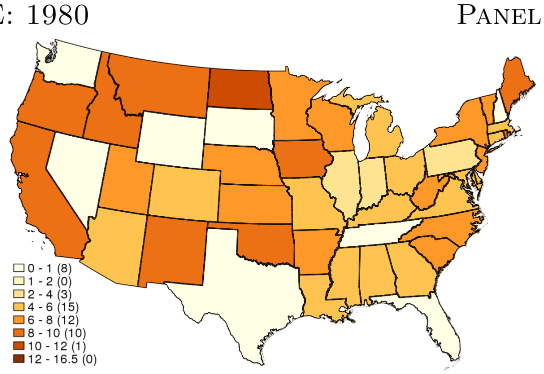
Panel D: 1970



Panel E: 1980



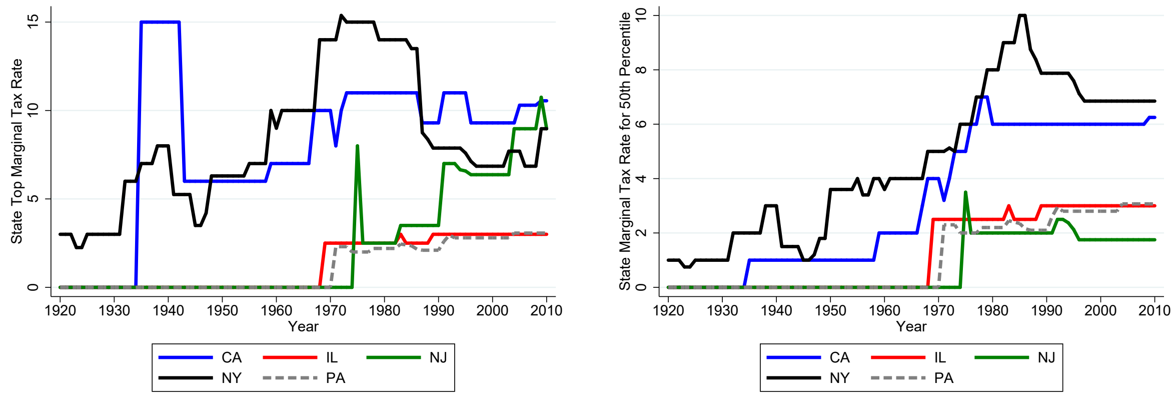
Panel F: 1990



Panel G: 2000

Notes: Figure plots the state statutory marginal personal income tax rates faced by individuals whose adjusted gross income is equal to the 90th percentile of the nation income distribution for men every ten years from 1940 through 2000. Darker colors indicate higher tax rates. Tax rates measured in percentage points.

Figure A8: The Evolution of Personal Income Taxes in Select States

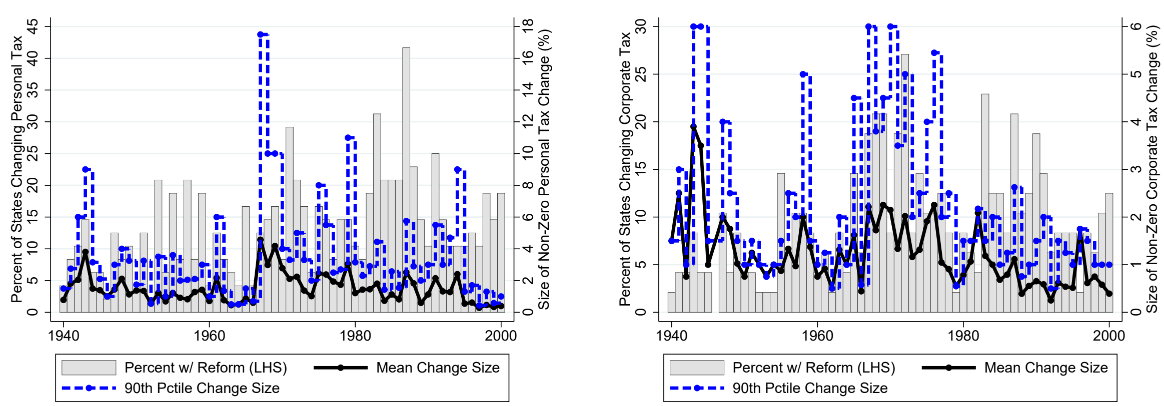


Panel A: Time Series of Key States' Top Statutory MTR

Panel B: Time Series of Key States' MTR for Median Earner

Notes: Figure plots the time series of marginal personal income tax rates for the five most innovative states in our sample. Tax rates are measured in percentage points. Panel A shows the top statutory personal income tax rate, while Panel B plots it for the median earner.

Figure A9: Trends in State Statutory Tax Policy Changes

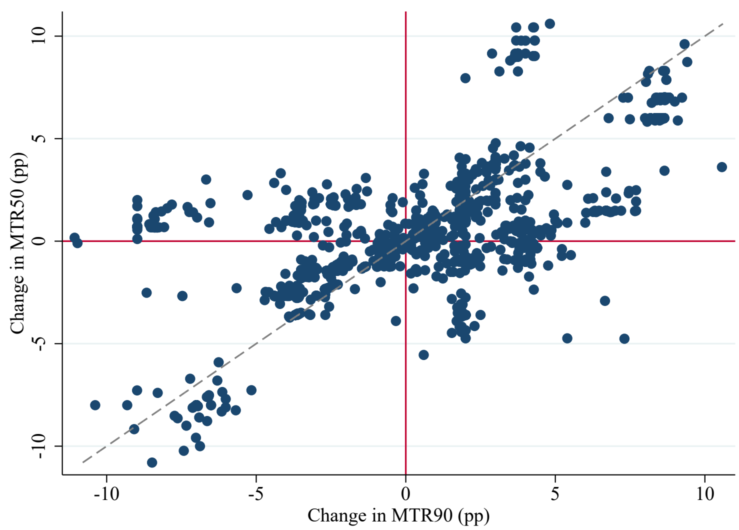


Panel A: Personal Income Tax

Panel B: Corporate Income Tax

Notes: Figure plots the time series of the share of states experiencing a statutory personal income (panel A) and corporate income (panel B) tax rate change. The gray bars, plotted against the left axis, show the share of all states that experience a statutory top tax rate change. The black solid line plots the mean size (positive or negative) of non-zero tax changes, while the blue dashed line represents the size of a 90^{th} percentile non-zero tax rate change in that year. Tax rate changes are measured in percentage points. Black and blue lines are plotted against the right axis.

Figure A10: Size of marginal tax rate changes for median and 90th percentile workers



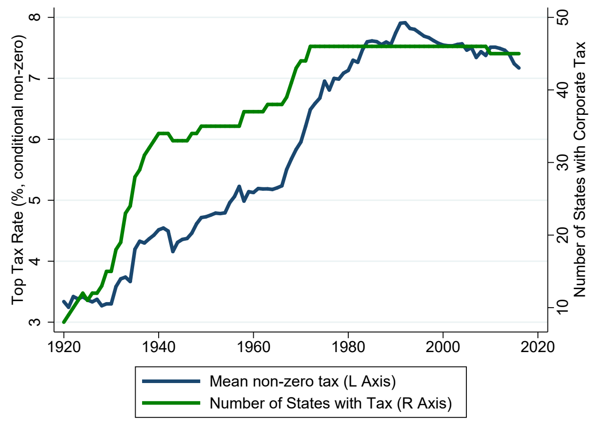
Notes: Figure is a scatter plot showing the relative size of tax rate changes for median versus 90th percentile workers. Each dot is a different state-year cell and the dashed line is a 45 degree line. Of the state-years that experience a change in the tax rate for either the 90th percentile or median worker, 44% had a larger change for top earners while 56% had a larger change for median earner.

Table A4: Share of Tax Changes Generated by Each Source

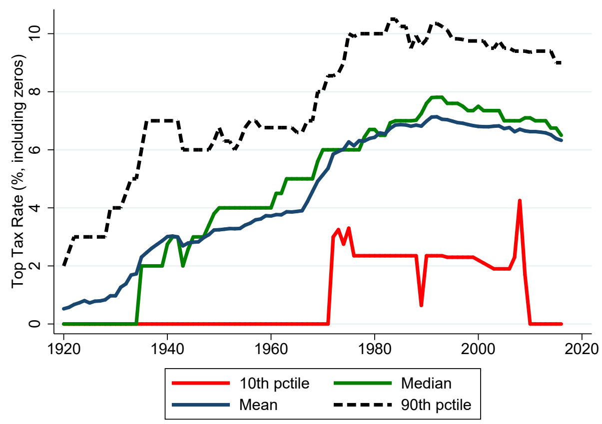
	Federal tax rate (1)	State tax rate (2)	Income distribution (3)
Personal tax rate for median earner	0.763	0.237	0.040
Personal tax rate for 90th percentile	0.783	0.217	0.046
Corporate top tax rate	0.766	0.288	–

Notes: Table reports the share of state-level changes in combined (i.e. federal plus state) tax liabilities that are caused by various forces. Column (1) reports the share of tax rate changes that are accompanied by a federal tax rate change. These changes may also be accompanied by state tax changes; indeed, since federal taxes are deductible for personal taxes in many states, nearly every change in federal tax change is associated with a change in personal state rates. Column (2) reports the share of tax rate changes that arise from changes in the statutory state tax rate. Since nearly all changes in personal federal tax rates are accompanied by state tax changes, column (2) only reports the share of changes that have no federal component for the personal tax rates. Thus column (1) and (2) add up to 1 in the first two rows. For corporate taxes, we report the share of changes that have a state-level component, regardless of whether federal taxes change as well. Finally, column (3) shows the share of personal income tax changes for percentile p that result from that percentile crossing across a tax bracket. We have no such tax bracket information for corporate taxes, thus this column is blank on the bottom row.

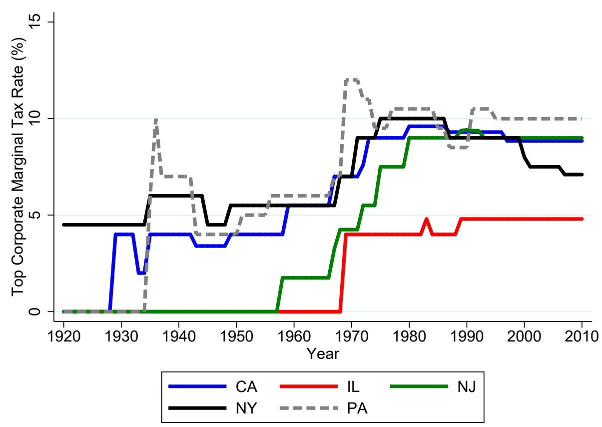
Figure A11: The Evolution of Corporate Taxes



Panel A: Intensive and Extensive Margin



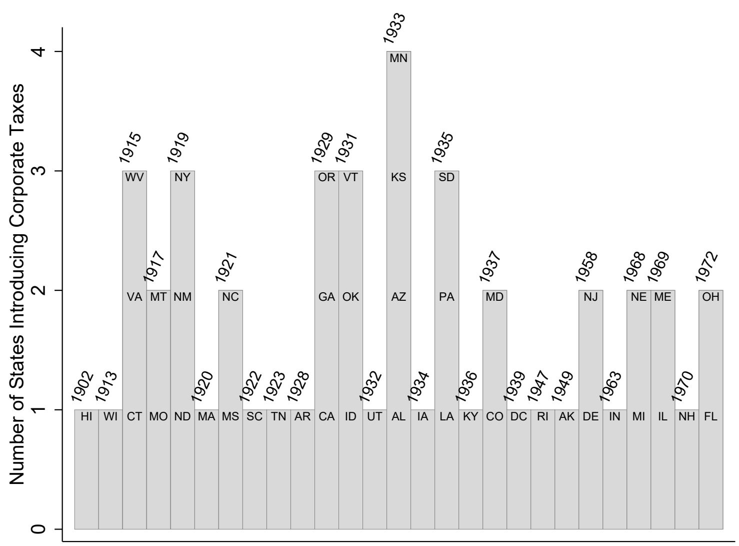
Panel B: Distribution of Statutory Tax Rates



Panel C: Time Series of Select States

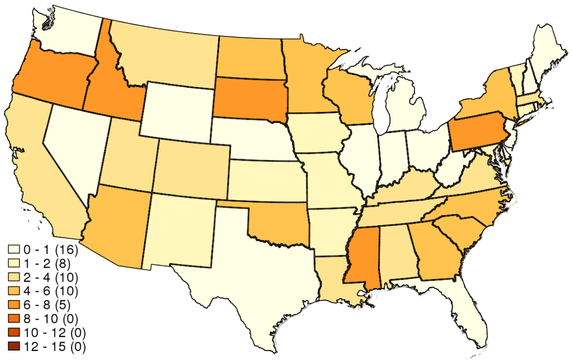
Notes: Figure plots the time series of the distribution and proliferation of state corporate tax rates. Panel A shows the number of states with a corporate income tax and the mean non-zero tax rate. Panel B plots the distribution of top state corporate tax rates over time. Panel C shows the evolution of top state corporate tax rates for the five most innovative states in our sample. All tax rates are measured in percentage points.

FIGURE A12: INTRODUCTION YEAR OF STATE CORPORATE TAXES

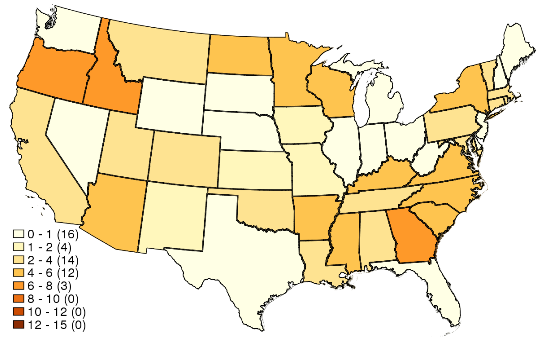


Notes: Figure plots the first year in which each state has a statutory corporate income tax rate.

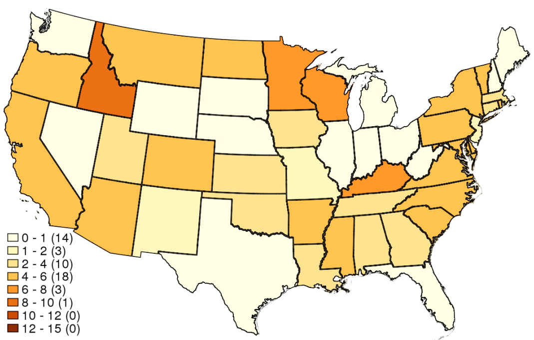
Figure A13: Top State Corporate Marginal Tax Rates over Time (Percentage Points)



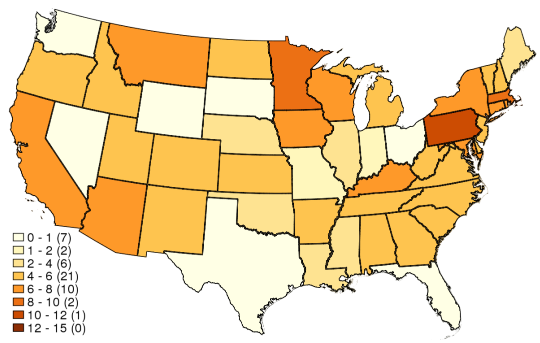
Panel A: 1940



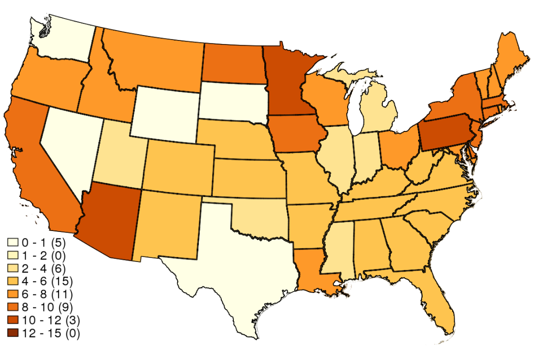
Panel B: 1950



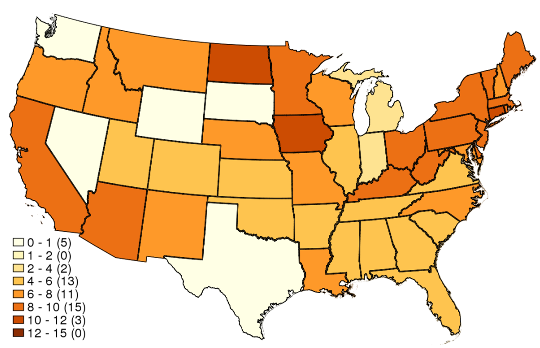
Panel C: 1960



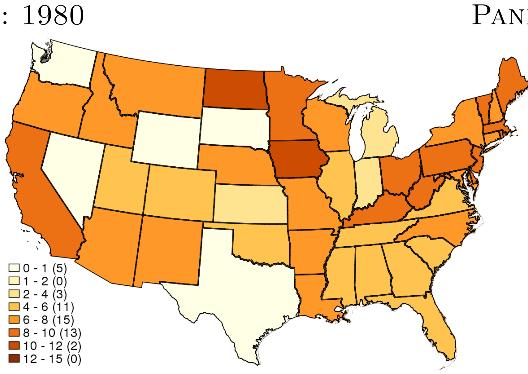
Panel D: 1970



Panel E: 1980



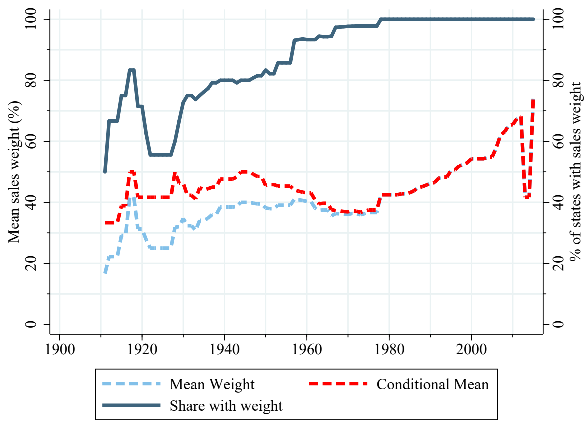
Panel F: 1990



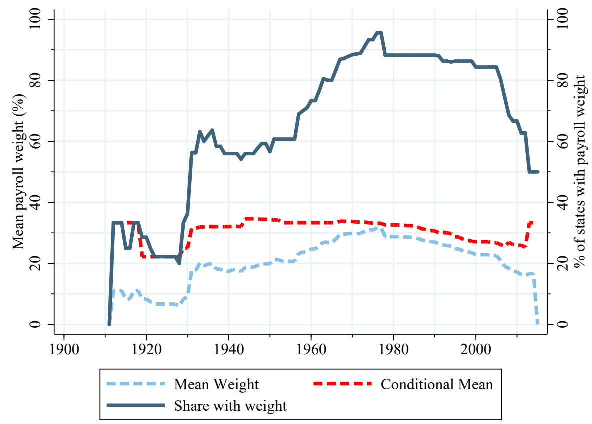
Panel G: 2000

Notes: Figure plots the state top statutory marginal corporate income tax rates every ten years from 1940 through 2000. Darker colors indicate higher tax rates. Tax rates measured in percentage points.

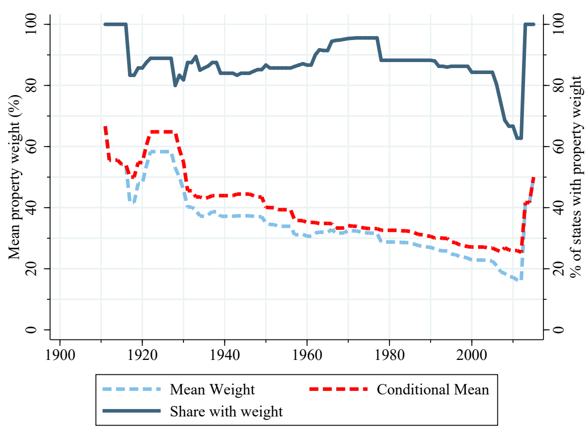
Figure A14: Evolution of State Corporate Income Apportionment Rules Through Time



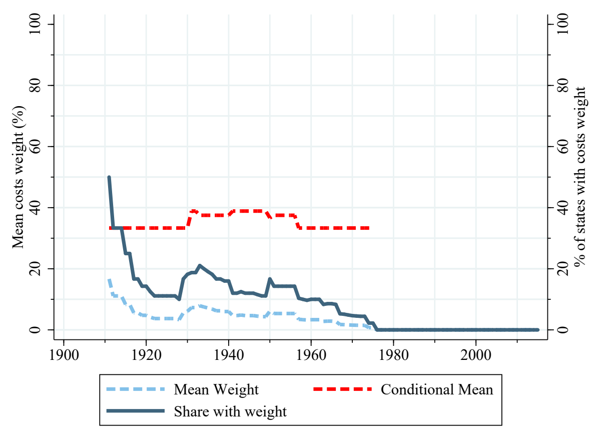
Panel A: Sales Weight



Panel B: Payroll Weight



Panel C: Property Weight

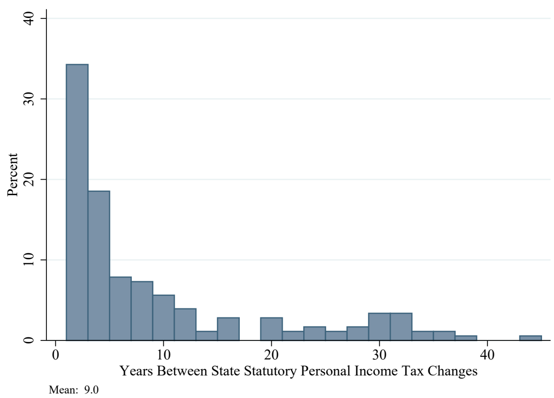


Panel D: Costs Weight

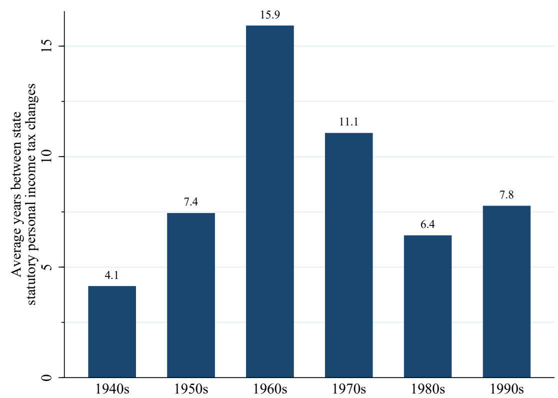
Notes: Figure plots the evolution of state corporate income tax apportionment rules. The solid blue lines plot the share of states that have at least some weight on a particular factor, conditional on having a corporate tax at all. The light blue dashed lines plot the average weight placed on the factor across all states with a corporate tax, while the red dashed lines plot the average weight placed on the factor by states which have at least some weight on that apportionment factor. Each panel considers a different apportionment factor. Data collection and definitions described in detail in Appendix OA.2.

Figure A15: Distribution of Time Between Large Tax Changes

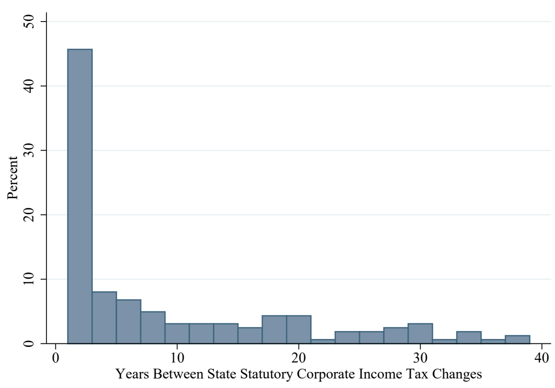
Panel A: Distribution of Time Between Large Top Statutory Personal Income Tax Changes



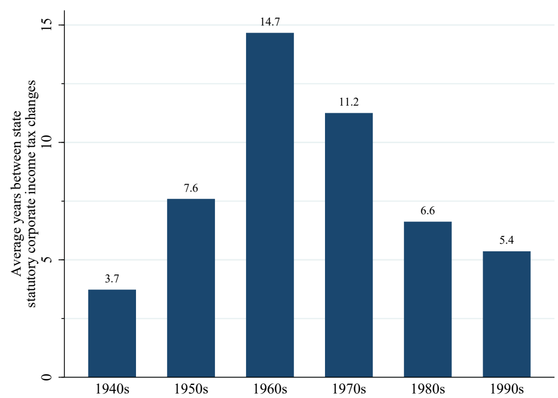
Panel B: Mean Time Between Large Top Statutory Personal Income Tax Changes



Panel C: Distribution of Time Between Large Top Statutory Corporate Income Tax Changes



Panel D: Mean Time Between Large Top Statutory Corporate Income Tax Changes



Notes: Figure summarized the number of years between large (i.e. top 10%) state tax reforms, the likes of which are used to define our event studies. Panels A and B consider state reforms to the top statutory personal tax rate, while Panels C and D consider state reforms to the top statutory corporate tax rate. Panels A and C show the distribution of times between large reforms, while Panels B and D show the average time between large reforms by decade. Decades are assigned to the second reform in a pair; for instance, if there is a reform in 1957 and 1962, a time gap of 5 would be coded in 1962.

A.3 Robustness and Extensions: State-Level Regressions

Table A5: State-level OLS regressions with all control coefficients reported

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	1.803***	1.516***	1.784***	0.056
	(0.450)	(0.507)	(0.427)	(0.071)
ln(1− Corp. MTR)	2.759***	2.382***	2.308***	0.573***
	(0.701)	(0.770)	(0.640)	(0.141)
Real Personal Income per Capita	0.069	0.308*	0.074	0.025
	(0.131)	(0.154)	(0.125)	(0.020)
Population Density	-0.009	0.002	-0.005	-0.010***
	(0.011)	(0.013)	(0.010)	(0.002)
R&D Tax Credit	0.001	0.010	0.002	0.002
	(0.010)	(0.013)	(0.009)	(0.002)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical to that table, but reports the coefficients additional control variables as well.

Table A6: State-level OLS regressions on additional outcomes

	Log Unadj. Citations (1)	Log Corp. Patents (2)	Log Non-Corp. Patents (3)	Log Mean Pat. Value (4)	Log Av. Estab. Emp. (5)
$\ln(1 - MTR90)$	1.527***	1.810***	1.080**	-0.859*	-0.045
	(0.512)	(0.552)	(0.419)	(0.437)	(0.236)
$\ln(1-$ Corp. MTR$)$	2.923***	4.000***	1.979***	1.791***	1.399***
	(0.832)	(0.915)	(0.547)	(0.556)	(0.367)
Observations	2867	2867	2867	2831	2867
R^2	0.96	0.95	0.96	0.75	0.87
Mean of Dep. Var.	9.55	6.71	5.68	3.02	3.98
S.D. of Dep. Var.	1.57	1.49	1.13	0.58	0.32

	Log Value Added (6)	Log Total Payroll (7)	Log Av. Weekly Earn. (8)	Log Income Per Capita (9)	Share in Manufact. (10)
$\ln(1 - MTR90)$	0.862	1.181**	0.129	0.296**	12.001***
	(0.556)	(0.548)	(0.118)	(0.113)	(4.473)
$\ln(1-$ Corp. MTR$)$	3.875***	3.438***	0.338***	0.747***	22.468***
	(0.681)	(0.689)	(0.125)	(0.165)	(7.621)
Observations	2867	2867	2867	2867	2844
R^2	0.95	0.95	0.96	0.98	0.93
Mean of Dep. Var.	8.74	7.96	4.64	8.08	25.15
S.D. of Dep. Var.	1.19	1.21	0.24	0.42	10.94

Notes: Table reports estimates from a state-level regression following equation (3), using alternative outcome variables. The outcome variables are as follows. Column (1) log total unadjusted citation counts; (2) Log number of patents assigned to corporations; (3) Log number of patents that are not assigned to corporations; (4) log average Kogan et al. (2017) patent value among patents applied for in that state; (5) Log average establishment size; (6) Log total state manufacturing value added; (7) Log total state manufacturing payrolls; (8) Log average weekly earnings of manufacturing employees in the state; (9) Log real per capita income; (10) Percent of workers in the manufacturing sector. Robust standard errors two-way clustered at state × five-year and year level in parentheses. All regressions control for lagged population density, real personal income per capita (excluded in column 9), R&D tax credits, state and year fixed effects and are weighted by state population in 1940. Tax rates are lagged by 3-years and measured as log net-of-tax rates. "ATRs" correspond to average tax rates, while "MTRs" correspond to marginal tax rates. Mainland states, excluding Louisiana, included for the period 1940-2000. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table A7: State-level OLS regressions using alternative tax rates

	Log Patents	Log Citations	Log Inventors	Share Assigned
$\ln(1 - MTR50)$	2.749**	2.738**	2.649**	-0.053
	(1.092)	(1.201)	(0.996)	(0.169)
ln(1− Corp. MTR)	2.783***	2.323***	2.345***	0.600***
	(0.745)	(0.813)	(0.678)	(0.146)
$\ln(1 - ATR90)$	3.396***	2.982**	3.323***	-0.113
	(1.084)	(1.202)	(1.001)	(0.173)
ln(1− Corp. MTR)	2.614***	2.235***	2.173***	0.612***
	(0.744)	(0.816)	(0.678)	(0.149)
$\ln(1 - ATR50)$	5.529***	5.457***	5.020***	0.139
	(1.803)	(2.015)	(1.632)	(0.288)
ln(1− Corp. MTR)	2.781***	2.326***	2.371***	0.577***
	(0.740)	(0.799)	(0.673)	(0.142)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except it includes the different personal income tax rates as independent variables. Each panel, separated by a horizontal line, reports separate sets of regressions. faced by both median ($MTR50$) and 90^{th} percentile earners as independent variables. "ATRs" correspond to average tax rates, while "MTRs" correspond to marginal tax rates.

Table A8: State-level OLS regressions including the personal marginal income tax rate for both median and 90^{th} percentile earners as independent variables

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	1.384***	1.031*	1.391***	0.086
	(0.447)	(0.517)	(0.438)	(0.069)
$\ln(1 - MTR50)$	1.668	1.932	1.561	-0.120
	(1.203)	(1.344)	(1.118)	(0.178)
ln(1− Corp. MTR)	2.574***	2.168***	2.135***	0.587***
	(0.719)	(0.798)	(0.653)	(0.147)
Observations	2867	2867	2867	2867
R^2 - Overall	0.96	0.96	0.97	0.87

Notes: See notes to Table 2. This table is identical except it includes the marginal personal income tax rate faced by both median ($MTR50$) and 90^{th} percentile earners as independent variables.

Table A9: State-level OLS regressions using tax rates for married individuals with two dependents

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	1.680***	1.599***	1.667***	0.053
	(0.493)	(0.549)	(0.476)	(0.074)
ln(1− Corp. MTR)	2.768***	2.293***	2.351***	0.546***
	(0.692)	(0.754)	(0.637)	(0.140)
Observations	2773	2773	2773	2773
Mean of Dep. Var.	7.08	9.67	7.10	0.72
S.D. of Dep. Var.	1.32	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except it uses the personal income tax rate faced by a married individual with two dependents, rather than a single individual with no dependents.

Table A10: State-level OLS regressions using tax rates which force itemized deductions

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	2.061***	1.735**	2.091***	-0.002
	(0.578)	(0.669)	(0.558)	(0.094)
ln(1− Corp. MTR)	2.784***	2.357***	2.358***	0.561***
	(0.712)	(0.773)	(0.652)	(0.140)
Observations	2773	2773	2773	2773
Mean of Dep. Var.	7.08	9.67	7.10	0.72
S.D. of Dep. Var.	1.32	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except it calculates the personal income tax rate assuming that all individuals itemize their deductions rather than taking the standard deduction if it is optimal to do so.

Table A11: State-level OLS regressions using Auerbach-Poterba Effective Federal Corporate Tax

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	1.702***	1.474***	1.636***	0.079
	(0.430)	(0.498)	(0.408)	(0.076)
ln(1− Corp. MTR)	3.048***	2.588***	2.673***	0.540***
	(0.788)	(0.851)	(0.724)	(0.159)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except, where possible, federal corporate tax rates are calculated using the effective Federal tax rate calculated by Auerbach and Poterba (1987) and updated by Auerbach (2007).

Table A12: State-level OLS regressions using alternative lags on tax rates

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
PANEL A: 1-YEAR LAGGED TAXES				
$\ln(1-MTR90)$	1.911***	1.695***	1.887***	0.082
	(0.499)	(0.577)	(0.475)	(0.072)
ln(1− Corp. MTR)	2.958***	2.495***	2.476***	0.604***
	(0.673)	(0.747)	(0.615)	(0.144)
PANEL B: 2-YEAR LAGGED TAXES				
$\ln(1-MTR90)$	1.845***	1.603***	1.819***	0.064
	(0.465)	(0.528)	(0.441)	(0.072)
ln(1− Corp. MTR)	2.847***	2.419***	2.380***	0.597***
	(0.688)	(0.761)	(0.627)	(0.148)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except it lags tax rates by different amounts. Tax rates are lagged by 1 year in Panel A and by 2 years in Panel B, compared with 3 years in Table 2.

Table A13: State-level OLS regressions with 10-year Newey-West standard errors

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	1.803***	1.516**	1.784***	0.056
	(0.642)	(0.717)	(0.613)	(0.089)
ln(1− Corp. MTR)	2.759***	2.382**	2.308***	0.573***
	(0.831)	(0.962)	(0.759)	(0.162)
R&D Tax Credit	0.076	0.994	0.219	0.168
	(1.415)	(1.821)	(1.309)	(0.214)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: See notes to Table 2. This table is identical except that Newey-West standard errors allowing for autocorrelation in errors for up to 10 years are reported in parentheses, rather than the baseline of standard errors two-way clustered at the state × five-year and year levels.

Table A14: State-level OLS regressions excluding New York and California

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	2.866***	2.861***	2.842***	0.050
	(0.546)	(0.603)	(0.493)	(0.112)
ln(1− Corp. MTR)	2.453***	1.891**	1.998***	0.567***
	(0.665)	(0.723)	(0.600)	(0.145)
Observations	2745	2745	2745	2745
Mean of Dep. Var.	6.79	9.35	6.81	0.72
S.D. of Dep. Var.	1.26	1.49	1.27	0.15

Notes: See notes to Table 2. This table is identical except that New York and California are dropped from the estimation sample.

Table A15: State-level OLS regressions excluding the 1970s

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	2.880***	3.151***	2.914***	0.020
	(0.655)	(0.739)	(0.600)	(0.139)
ln(1− Corp. MTR)	3.511***	2.732***	2.863***	0.791***
	(0.819)	(0.923)	(0.758)	(0.180)
Observations	2250	2250	2250	2250
Mean of Dep. Var.	6.79	9.38	6.80	0.71
S.D. of Dep. Var.	1.27	1.54	1.29	0.16

Notes: See notes to Table 2. This table is identical except that the 1970s are dropped from the estimation sample.

Table A16: State-level regressions including sample from 1940-2010

PANEL A: OLS with Fixed Effects	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	2.414***	2.019***	2.309***	0.127*
	(0.514)	(0.579)	(0.488)	(0.075)
ln(1− Corp. MTR)	3.578***	2.909***	3.044***	0.681***
	(0.754)	(0.799)	(0.684)	(0.148)
Observations	3337	3337	3337	3337
Mean of Dep. Var.	7.20	9.87	7.23	0.74
S.D. of Dep. Var.	1.35	1.65	1.37	0.15

PANEL B: 20-YEAR LONG DIFFERENCE				
Δ MTR90	1.534***	1.153**	1.529***	0.121
	(0.446)	(0.531)	(0.440)	(0.072)
Δ Corp. MTR	1.894***	1.773***	1.606***	0.416***
	(0.521)	(0.620)	(0.488)	(0.130)
Observations	2397	2397	2397	2397
Mean of Dep. Var.	0.42	0.90	0.53	0.10
S.D. of Dep. Var.	0.54	0.83	0.49	0.11

PANEL C: 15-YEAR LONG DIFFERENCE				
Δ MTR90	1.162***	0.828**	1.239***	0.074
	(0.362)	(0.403)	(0.350)	(0.061)
Δ Corp. MTR	1.276***	0.872	1.053**	0.291***
	(0.460)	(0.578)	(0.444)	(0.106)
Observations	2632	2632	2632	2632
Mean of Dep. Var.	0.33	0.64	0.41	0.08
S.D. of Dep. Var.	0.47	0.79	0.43	0.10

PANEL D: 10-YEAR LONG DIFFERENCE				
Δ MTR90	0.819**	0.660	0.879**	0.079
	(0.375)	(0.414)	(0.374)	(0.050)
Δ Corp. MTR	0.969**	0.621	0.897**	0.132
	(0.422)	(0.536)	(0.435)	(0.111)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	0.21	0.38	0.26	0.05
S.D. of Dep. Var.	0.36	0.65	0.34	0.08

Notes: Table reports estimates from state-level regressions over the sample 1940-2010. Panel A estimates the regression following equation (3), while Panels B-D estimate long-difference regressions following equation (4). See notes to Tables 2 and 3 for more details.

Table A17: State-level OLS including controls for state political leaning

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	1.087**	0.743	1.104***	-0.026
	(0.421)	(0.449)	(0.395)	(0.079)
ln(1− Corp. MTR)	2.100***	2.185***	1.790***	0.589***
	(0.592)	(0.651)	(0.537)	(0.148)
State Governor: Democrat	0.062***	0.061**	0.059***	0.004
	(0.021)	(0.024)	(0.020)	(0.004)
% State Upper House Democrat	0.001	0.001	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.000)
% State Lower House Democrat	-1.217***	-1.212***	-1.110***	-0.147***
	(0.179)	(0.208)	(0.165)	(0.025)
Observations	2764	2764	2764	2764
Mean of Dep. Var.	7.10	9.69	7.12	0.72
S.D. of Dep. Var.	1.31	1.55	1.33	0.14

Notes: See notes to Table 2. This table is identical except that it includes additional political controls, specifically the party of the state governor, and the percent of the state legislature which is Democrat.

Table A18: State-level OLS regressions including fixed effects but excluding all controls

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1-MTR90)$	1.770***	1.616***	1.771***	0.031
	(0.441)	(0.482)	(0.417)	(0.075)
ln(1− Corp. MTR)	2.910***	2.136***	2.359***	0.804***
	(0.649)	(0.694)	(0.582)	(0.151)
Observations	2914	2914	2914	2914
Mean of Dep. Var.	7.06	9.64	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.35	0.15

Notes: See notes to Table 2. This table is identical except that it drops all controls from the regression, but continues to include state and year fixed effects.

Table A19: Unweighted state-level OLS regressions

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	2.083***	1.850***	2.004***	0.025
	(0.399)	(0.470)	(0.385)	(0.081)
ln(1− Corp. MTR)	1.452**	1.683**	1.079*	0.519***
	(0.660)	(0.749)	(0.605)	(0.148)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	6.04	8.62	6.06	0.66
S.D. of Dep. Var.	1.44	1.70	1.46	0.18

Notes: See notes to Table 2. This table is identical except that it does not weight states by their 1940 population.

Table A20: First Stage of Core Macro Instrumental Variables regression: 5-year Lagged Income Distribution

Dep. Var.:	MTR - 90^{th} (1)	Top Corp. MTR (2)	MTR - 50^{th} (3)	Top Corp. MTR (4)
90th Pctile Income MTR Instr	0.650***	-0.014		
	(0.081)	(0.025)		
Median Income MTR Instr			0.779***	-0.046
			(0.043)	(0.035)
Top Corporate MTR Instr	0.060	0.752***	0.063**	0.756***
	(0.055)	(0.060)	(0.025)	(0.060)
	(0.001)	(0.000)	(0.000)	(0.000)
Observations	2867	2867	2867	2867
R^2	0.366	0.605	0.592	0.606

Notes: Table reports the first stage regression of the state-level instrumental variables regression reported in Panel C of Table 2. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by equations (6) and (8) respectively. Standard errors two-way clustered at state × five-year and year level are reported in parentheses below point estimate. IV convolves five-year lags of both the state tax law and income distribution with current federal tax rates. All regressions include controls for lagged personal income per capita, population density, and R&D Tax Credits, as well as state and year fixed effects. Each column corresponds to a different dependent variable.

Table A21: Alternative Macro Instrumental Variables regression using Unlagged Income Distribution

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	2.206***	1.813**	2.126***	0.054
	(0.633)	(0.718)	(0.595)	(0.091)
ln(1− Corp. MTR)	3.570***	2.849***	3.067***	0.588***
	(0.908)	(1.009)	(0.834)	(0.200)
Observations	2867	2867	2867	2867
Mean of Dep. Var.	7.07	9.65	7.08	0.72
S.D. of Dep. Var.	1.33	1.56	1.34	0.14

Notes: Table reports estimates from an instrumental variables regression following equation (3). The specification in this table is identical to that in Panel C of Table 2, except that it does not lag the income distribution when constructing the instrument. That is, the instruments use current federal tax law and five-year lagged state tax laws, using an unlagged income distribution.

Table A22: First Stage of Alternative Macro Instrumental Variables regression using Unlagged Income Distribution

Dep. Var.:	MTR - 90^{th} (1)	Top Corp. MTR (2)	MTR - 50^{th} (3)	Top Corp. MTR (4)
90th Pctile Income MTR Instr	0.847***	-0.018		
	(0.038)	(0.028)		
Median Income MTR Instr			0.720***	-0.039
			(0.038)	(0.030)
Top Corporate MTR Instr	0.017	0.753***	0.035*	0.757***
	(0.035)	(0.060)	(0.020)	(0.060)
R&D Tax Credit	-0.000	-0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2867	2867	2867	2867
R^2	0.697	0.606	0.706	0.606

Notes: Table reports the first stage regression of the state-level instrumental variables using an unlagged income distribution, as in Table A21 above.

Table A23: Time Series Regressions on Federal Tax Rates

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Share Assigned (4)
$\ln(1 - MTR90)$	1.896***	2.494***	1.875***	0.071
	(0.226)	(0.228)	(0.240)	(0.045)
$\ln(1-$ Corp $\text{MTR}^{AP})$	0.111	0.463**	0.512	0.073
	(0.334)	(0.190)	(0.307)	(0.093)
Trend	0.067***	0.163***	0.077***	0.003
	(0.010)	(0.016)	(0.012)	(0.004)
$\ln(Income/Cap)$	-2.108***	-4.274***	-2.342***	-0.066
	(0.402)	(0.654)	(0.515)	(0.168)
Observations	39	39	39	39

Notes: Table reports estimates from time series regressions of aggregate innovation measures on federal tax rates. "$MTR90$" corresponds to the federal tax rate that would apply to someone whose adjusted gross income is equal to the 90^{th} percentile of income in the US in that year, while "Corp. MTR^{AP}" represents to the effective federal corporate tax rate as calculated by Auerbach and Poterba (1987). Tax rates are lagged by three years. "Trend" is a linear trend, while $Income/Cap$ is aggregate personal income per capita, lagged by one year. Newey-West standard errors allowing for up to 10-years of serial correlation are reported in parentheses. Auerbach-Poterba corporate tax rates are not available before 1959; therefore, the sample consists of all years from 1962-2000.

A.4 Robustness and Extensions: Inventor-Level Regressions

Table A24: Effects of Taxes at the Individual Inventor Level (IV)

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.616***	0.490***	0.855***	1.340***	0.246**
	(0.063)	(0.060)	(0.140)	(0.157)	(0.092)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.353	0.404	0.504	0.622	0.737
ln(1− Personal MTR)	0.554***	0.427***	0.791***	1.075***	0.367***
	(0.051)	(0.056)	(0.134)	(0.146)	(0.069)
ln(1− Corp. MTR)	-0.257	-0.227	-0.781*	-1.161*	-0.090
	(0.163)	(0.166)	(0.406)	(0.638)	(0.191)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5634789	5634789	3576456	3459553	1150717
Mean of Dep. Var.	0.638	0.414	0.602	2.958	0.609
S.D. of Dep. Var.	0.481	0.492	0.709	1.470	0.488
R^2	0.358	0.405	0.493	0.624	0.729

Notes: See the notes to Table 4. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by equations (6) and (8) respectively. That is, the instruments use current federal tax law and five-year lagged state tax laws, using a five-year lagged income distribution. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A25: First Stage of Core Inventor-level Instrumental Variables Regression

LHS Tax:	Personal (1)	Personal (2)	Corporate (3)
Personal MTR Instrument	0.918***	0.988***	-0.017
	(0.076)	(0.086)	(0.015)
Corporate MTR Instrument	0.029		0.396***
	(0.051)		(0.097)
State × Year FE	N	Y	N
Inventor FE	Y	Y	Y
Observations	6899376	8305203	8287859
Mean of Dep. Var.	-0.246	-0.245	-0.571
S.D. of Dep. Var.	0.115	0.109	0.157
R^2	0.881	0.924	0.221

Notes: Table reports the first stage regression of the inventor-level instrumental variables. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by equations (6) and (8) respectively. All tax rates are input as log retention rates, so if the tax rate is τ, the dependent variable and instrument are included in the regression as $\ln(1-\tau)$. Standard errors two-way clustered at state and year level are reported in parentheses below point estimate. IV convolves five-year lags of both the income distribution and the inventor's residence state tax law with current federal tax rates. See notes to Table 4 for list of control variables. Columns 1 and 2 have the personal marginal tax rate as the dependent variable, while column 3 uses the top corporate marginal tax rate as a dependent variable.

Table A26: Inventor-level OLS regressions defining counting inventors as being high quality if they are in the top 5% of patent counts

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.425***	0.367***	0.672***	0.728***	0.482***
	(0.058)	(0.056)	(0.176)	(0.186)	(0.114)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.420	0.516	0.578	0.715	0.806
ln(1− Personal MTR)	0.448***	0.417***	0.849***	1.109***	0.288***
	(0.051)	(0.055)	(0.162)	(0.170)	(0.068)
ln(1− Corp. MTR)	0.080	0.074	0.093	0.120	0.004
	(0.065)	(0.064)	(0.118)	(0.219)	(0.109)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.420	0.517	0.578	0.716	0.808

Notes: See notes to Table 4. This table is identical except it defines inventors to be high quality if they belong to the top 5% of the distribution of cumulative patent counts, rather than the top 10%.

Table A27: Inventor-level OLS regressions defining counting inventors as being high quality if they are in the top 25% of patent counts

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.391***	0.352***	0.687***	1.075***	0.186**
	(0.062)	(0.055)	(0.121)	(0.136)	(0.086)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.422	0.519	0.581	0.718	0.809
ln(1− Personal MTR)	0.369***	0.330***	0.661***	0.982***	0.198**
	(0.056)	(0.051)	(0.106)	(0.125)	(0.079)
ln(1− Corp. MTR)	0.077	0.075	0.103	0.109	0.010
	(0.061)	(0.059)	(0.104)	(0.205)	(0.110)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.421	0.518	0.579	0.717	0.807

Notes: See notes to Table 4. This table is identical except it defines inventors to be high quality if they belong to the top 25% of the distribution of cumulative patent counts, rather than the top 10%.

Table A28: Inventor-level OLS regressions using three inventor quality levels

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.426***	0.348***	0.694***	1.066***	0.224***
	(0.067)	(0.051)	(0.095)	(0.112)	(0.048)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.382	0.427	0.538	0.659	0.771
ln(1− Personal MTR)	0.406***	0.330***	0.666***	0.970***	0.220***
	(0.061)	(0.047)	(0.082)	(0.102)	(0.045)
ln(1− Corp. MTR)	0.069	0.072	0.098	0.121	-0.043
	(0.057)	(0.052)	(0.090)	(0.186)	(0.088)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	4669149	4669149	2795112	2714189	908602
Mean of Dep. Var.	0.599	0.386	0.598	2.961	0.661
S.D. of Dep. Var.	0.490	0.487	0.726	1.494	0.473
R^2	0.381	0.426	0.536	0.658	0.769

Notes: See notes to Table 4. This table is identical except it assigns inventors to three quality levels. Personal MTR in this table is defined as the marginal tax rate faced by the 90^{th} percentile earner in state s in year t for high productivity inventors (top decile of lagged patent counts), by the 75^{th} percentile earner for middle productivity inventors (between the 75th and 90th percentiles of lagged patent counts) and the marginal tax rate rate faced by the median earner for low productivity inventors.

Table A29: Inventor-level OLS regressions ranking inventors according to their cumulative citation counts

Dependent Variable:	Has Patent	Has 10+ Cites	Log Patents	Log Citations	Has High-Value Pat.
	(1)	(2)	(3)	(4)	(5)
ln(1− Personal MTR)	0.343***	0.322***	0.545***	0.866***	0.111
	(0.067)	(0.075)	(0.159)	(0.204)	(0.077)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.420	0.517	0.577	0.718	0.808
ln(1− Personal MTR)	0.317***	0.294***	0.530***	0.783***	0.154**
	(0.057)	(0.066)	(0.142)	(0.174)	(0.070)
ln(1− Corp. MTR)	0.103	0.097	0.149	0.178	0.028
	(0.068)	(0.068)	(0.122)	(0.231)	(0.112)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.419	0.516	0.576	0.717	0.807

Notes: See notes to Table 4. This table is identical except it defines inventors to be high quality if they belong to the top 10% of the distribution of cumulative citation counts, rather than the top 10% of cumulative patent counts.

Table A30: Inventor-level OLS regressions interacting MTR90 with percentile bins of inventor quality

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Cites (4)	Has High-Value Pat. (5)
ln(1− MTR90) × 50th-75th	0.149**	0.080**	0.097***	0.210***	-0.055**
	(0.056)	(0.035)	(0.033)	(0.043)	(0.025)
ln(1− MTR90) × 75th-90th	0.300***	0.194***	0.313***	0.580***	0.005
	(0.091)	(0.062)	(0.077)	(0.103)	(0.038)
ln(1− MTR90) × 90th-95th	0.420***	0.288***	0.527***	0.837***	0.099*
	(0.104)	(0.072)	(0.112)	(0.139)	(0.053)
ln(1− MTR90) × 95th-99th	0.565***	0.448***	0.890***	1.325***	0.181***
	(0.117)	(0.083)	(0.151)	(0.176)	(0.059)
ln(1− MTR90) × 99th+	0.735***	0.679***	1.696***	2.270***	0.269***
	(0.133)	(0.112)	(0.246)	(0.293)	(0.070)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.393	0.439	0.549	0.667	0.782
ln(1− MTR90) × 50th-75th	0.142***	0.077**	0.091***	0.175***	-0.050**
	(0.051)	(0.031)	(0.027)	(0.043)	(0.020)
ln(1− MTR90) × 75th-90th	0.291***	0.189***	0.296***	0.526***	0.013
	(0.084)	(0.057)	(0.068)	(0.095)	(0.032)
ln(1− MTR90) × 90th-95th	0.410***	0.281***	0.500***	0.768***	0.107**
	(0.097)	(0.067)	(0.105)	(0.129)	(0.047)
ln(1− MTR90) × 95th-99th	0.553***	0.440***	0.858***	1.254***	0.191***
	(0.110)	(0.079)	(0.144)	(0.167)	(0.056)
ln(1− MTR90) × 99th+	0.722***	0.671***	1.665***	2.204***	0.281***
	(0.128)	(0.110)	(0.239)	(0.290)	(0.065)
ln(1− Corp. MTR)	0.090	0.098*	0.168	0.227	-0.005
	(0.060)	(0.056)	(0.107)	(0.191)	(0.088)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	4777949	4777949	2883935	2798747	940657
Mean of Dep. Var.	0.604	0.387	0.588	2.943	0.652
S.D. of Dep. Var.	0.489	0.487	0.723	1.490	0.476
R^2	0.392	0.438	0.546	0.666	0.780

Notes: Table reports estimated coefficients from regression which interacts the marginal tax rate faced by an individual at the 90^{th} percentile of the income distribution with percentile bins of the inventor cumulative patents distribution. Regressions also include indicators for inventor quality bins, but are otherwise identical to that in Table 4. Estimated coefficients represent (semi-)elasticities of innovation to the marginal tax rate faced by a 90^{th} percentile earner in the inventor's residence state, relative inventors in the bottom 50% of the inventor quality distribution, who serve as a control. The upper bound elasticity of innovation to taxes is the coefficient on $\ln(1-MTR90)\times$ 99th+. A lower bound on the elasticity is this coefficient minus the coefficient on $\ln(1-MTR90)\times$ 95th-99th.

Table A31: Inventor-level OLS regressions excluding New York and California

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.495***	0.447***	0.902***	1.233***	0.323***
	(0.070)	(0.069)	(0.171)	(0.186)	(0.086)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.428	0.523	0.581	0.717	0.813
ln(1− Personal MTR)	0.454***	0.410***	0.849***	1.133***	0.338***
	(0.060)	(0.061)	(0.153)	(0.165)	(0.078)
ln(1− Corp. MTR)	0.052	0.044	-0.022	0.021	0.006
	(0.060)	(0.059)	(0.085)	(0.212)	(0.124)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	4910129	4910129	3467757	3350408	1126399
Mean of Dep. Var.	0.706	0.416	0.448	2.735	0.497
S.D. of Dep. Var.	0.455	0.493	0.654	1.428	0.500
R^2	0.426	0.522	0.580	0.716	0.811

Notes: See notes to Table 4. This table is identical except it drops inventors living in New York and California from the estimation sample.

Table A32: Inventor-level OLS regressions excluding the 1970s

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.395***	0.319***	0.543***	0.915***	0.124
	(0.089)	(0.085)	(0.195)	(0.222)	(0.109)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.434	0.533	0.600	0.735	0.812
ln(1− Personal MTR)	0.359***	0.286***	0.523***	0.827*	0.157
	(0.074)	(0.075)	(0.172)	(0.460)	(0.100)
ln(1− Corp. MTR)	0.159	0.196**	0.400**	0.413	0.147
	(0.100)	(0.097)	(0.166)	(1.269)	(0.181)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5516741	5516741	3920471	3786699	1244162
Mean of Dep. Var.	0.711	0.431	0.472	2.833	0.500
S.D. of Dep. Var.	0.453	0.495	0.674	1.485	0.500
R^2	0.433	0.533	0.599	0.735	0.811

Notes: See notes to Table 4. This table is identical except it drops the 1970s from the estimation sample.

Table A33: Inventor-level OLS regressions including sample from 1940-2010

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.339***	0.340***	0.497**	0.963***	0.226**
	(0.082)	(0.074)	(0.205)	(0.209)	(0.089)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.386	0.501	0.576	0.684	0.800
ln(1− Personal MTR)	0.308***	0.300***	0.481**	0.826***	0.242***
	(0.070)	(0.069)	(0.185)	(0.197)	(0.083)
ln(1− Corp. MTR)	0.130*	0.127*	0.198	0.481	-0.025
	(0.067)	(0.074)	(0.141)	(0.314)	(0.082)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	9302817	9302817	6815887	6196303	2215801
Mean of Dep. Var.	0.733	0.410	0.518	2.832	0.500
S.D. of Dep. Var.	0.443	0.492	0.715	1.602	0.500
R^2	0.385	0.500	0.574	0.682	0.799

Notes: Table reports estimates from inventor-level regressions over the sample 1940-2010. Regression is identical to that in Table 4 except for the expanded sample. See notes to that table for more details.

Table A34: Inventor-level OLS regressions using tax rates for a married couple with two dependents

Dependent Variable:	Has Patent	Has 10+ Cites	Log Patents	Log Citations	Has High-Value Pat.
	(1)	(2)	(3)	(4)	(5)
ln(1− Personal MTR)	0.324***	0.310***	0.585***	0.888***	0.156
	(0.067)	(0.064)	(0.158)	(0.167)	(0.101)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.421	0.518	0.580	0.719	0.809
ln(1− Personal MTR)	0.294***	0.273***	0.539***	0.759***	0.173*
	(0.053)	(0.052)	(0.138)	(0.146)	(0.095)
ln(1− Corp. MTR)	0.084	0.075	0.108	0.137	0.016
	(0.063)	(0.063)	(0.118)	(0.214)	(0.116)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6344207	6344207	4491944	4345516	1472687
Mean of Dep. Var.	0.708	0.424	0.458	2.785	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.457	0.500
R^2	0.420	0.517	0.579	0.718	0.808

Notes: See notes to Table 4. This table is identical except it uses the tax rate faced by a married couple with two dependents, rather than the tax rate faced by a single individual. To calculate the married tax rate, we assume that an earner at the j^{th} percentile has a spouse who earns 50% as much as the j^{th} percentile.

Table A35: Inventor-level OLS regressions excluding inventor fixed effects

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.135***	0.263***	0.093	0.112	-0.212***
	(0.029)	(0.022)	(0.105)	(0.167)	(0.070)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	N	N	N	N	N
R^2	0.154	0.094	0.114	0.173	0.163
ln(1− Personal MTR)	0.141***	0.247***	0.116	0.137	-0.150**
	(0.026)	(0.025)	(0.096)	(0.172)	(0.059)
ln(1− Corp. MTR)	0.078	0.108	0.132	0.186	-0.099
	(0.060)	(0.115)	(0.195)	(0.614)	(0.279)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	N	N	N	N	N
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.153	0.092	0.111	0.169	0.156

Notes: See notes to Table 4. This table is identical except it excludes inventor fixed effects.

Table A36: Inventor-level OLS regressions excluding all control variables

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.397***	0.321***	0.611***	0.710***	0.445***
	(0.053)	(0.051)	(0.138)	(0.133)	(0.127)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.420	0.517	0.578	0.716	0.805
ln(1− Personal MTR)	0.353***	0.286***	0.574***	0.650***	0.444***
	(0.045)	(0.045)	(0.121)	(0.113)	(0.112)
ln(1− Corp. MTR)	0.179*	0.161*	0.297	0.225	-0.025
	(0.101)	(0.093)	(0.218)	(0.247)	(0.109)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6465423	6465423	4569456	4418422	1485861
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.419	0.516	0.576	0.715	0.804

Notes: Table reports estimates from an inventor-level OLS regression, similar to Table 4 only excluding all control variables. See notes to that table for details. Regressions only include controls for inventor quality and the listed fixed effects.

Table A37: Inventor-level OLS regressions, using state tax laws from the inventor's home state

Dependent Variable:	Has Patent	Has 10+ Cites	Log Patents	Log Citations	Has High-Value Pat.
	(1)	(2)	(3)	(4)	(5)
ln(1− Personal MTR)	0.440***	0.383***	0.745***	1.022***	0.251***
	(0.061)	(0.058)	(0.149)	(0.154)	(0.084)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.421	0.518	0.580	0.717	0.809
ln(1− Personal MTR)	0.421***	0.365***	0.727***	0.974***	0.268***
	(0.058)	(0.056)	(0.141)	(0.145)	(0.080)
ln(1− Corp. MTR)	0.106	0.102	0.162	0.208	0.029
	(0.068)	(0.066)	(0.120)	(0.227)	(0.109)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460334	6460334	4566357	4415457	1485479
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.420	0.517	0.578	0.717	0.807

Notes: Table reports estimates from an inventor-level OLS regression, similar to Table 4. See notes to that table for details. The only difference to that table is that tax rates correspond to an inventor's home state – the state in which they first apply for a patent.

Table A38: Alternative Inventor-level IV regressions, using state tax laws from inventors' home state

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.636***	0.505***	0.880***	1.406***	0.291***
	(0.075)	(0.067)	(0.152)	(0.170)	(0.087)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.353	0.404	0.504	0.622	0.737
ln(1− Personal MTR)	0.590***	0.456***	0.841***	1.191***	0.381***
	(0.066)	(0.062)	(0.149)	(0.155)	(0.072)
ln(1− Corp. MTR)	-0.274	-0.241	-0.805*	-1.218*	-0.097
	(0.165)	(0.168)	(0.413)	(0.647)	(0.192)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5634718	5634718	3576424	3459521	1150707
Mean of Dep. Var.	0.638	0.414	0.602	2.958	0.609
S.D. of Dep. Var.	0.481	0.492	0.709	1.470	0.488
R^2	0.358	0.405	0.493	0.624	0.729

Notes: See notes to Table A24. This table is identical except that the instruments use current federal tax law and five-year lagged home state tax laws, using a five-year lagged income distribution, rather than the inventor's current residence state.

Table A39: First Stage of Alternative Inventor-level IV using state tax laws from inventors' home state

LHS Tax:	Personal (1)	Personal (2)	Corporate (3)
Personal MTR Instrument	0.847***	0.843***	-0.015
	(0.068)	(0.063)	(0.011)
Corporate MTR Instrument	0.098		0.395***
	(0.065)		(0.097)
State × Year FE	N	Y	N
Inventor FE	Y	Y	Y
Observations	6899298	8305081	8287738
Mean of Dep. Var.	-0.246	-0.245	-0.571
S.D. of Dep. Var.	0.115	0.109	0.157
R-Squared	0.853	0.897	0.220

Notes: Table presents first stage estimates for the inventor-level instrumental variable using the state tax laws of the inventor's home state. See notes to Tables A25 and A38.

Table A40: Inventor-level OLS Regressions Allowing Coefficients to Vary pre versus post 1970

Dependent Variable:	Has Patent	Has 10+ Cites	Log Patents	Log Citations	Has High-Value Pat.
	(1)	(2)	(3)	(4)	(5)
$\ln(1-MTR90)\times$ 1940-1969	0.629***	0.612***	1.023***	1.360***	0.059
	(0.123)	(0.135)	(0.330)	(0.375)	(0.117)
$\ln(1-MTR90)\times$ 1970-2000	0.122*	0.148**	0.349**	0.422**	0.052
	(0.066)	(0.056)	(0.149)	(0.182)	(0.088)
ln(1−Corp. MTR) × 1940-1969	0.087	0.192**	0.299	0.774**	-0.032
	(0.071)	(0.091)	(0.180)	(0.323)	(0.211)
ln(1−Corp. MTR) × 1970-2000	0.122*	0.106*	0.168	0.211	0.027
	(0.065)	(0.056)	(0.112)	(0.149)	(0.115)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.42	0.52	0.58	0.72	0.81
$\ln(1-MTR90)\times$ 1940-1969	0.669***	0.569***	1.028***	1.063***	0.712***
	(0.144)	(0.137)	(0.345)	(0.331)	(0.184)
$\ln(1-MTR90)\times$ 1970-2000	0.059	0.142**	0.318**	0.688***	-0.226
	(0.063)	(0.059)	(0.152)	(0.200)	(0.180)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6465345	6465345	4569398	4418390	1485854
Mean of Dep. Var.	0.71	0.42	0.46	2.78	0.50
S.D. of Dep. Var.	0.46	0.49	0.66	1.45	0.50
R^2	0.42	0.52	0.58	0.72	0.81

Notes: Table reports inventor-level OLS regressions which allow the effect of taxes to be different before and after 1970. We augment regression (12) by interacting tax rates with indicators for whether the time period t is before or after 1970. Otherwise, the specification is identical to that of Table 4. See footnotes to that table for more information.

Table A41: Inventor-level OLS regressions showing the effect of agglomeration on tax elasticities, controlling for state patenting in any class

Dependent Variable:	Has Patent (1)	Has 10+ Cites (2)	Log Patents (3)	Log Citations (4)	Has High-Value Pat. (5)
ln(1− Personal MTR)	0.247	0.375**	0.828**	1.297***	-0.025
	(0.210)	(0.172)	(0.375)	(0.448)	(0.213)
ln(1− Personal MTR) × Agglom.	-0.247***	-0.313***	-0.420***	-0.698***	-0.034
	(0.086)	(0.078)	(0.152)	(0.199)	(0.040)
State Patents × ln(1− Personal MTR)	0.030	0.008	0.002	-0.012	0.035*
	(0.022)	(0.018)	(0.039)	(0.050)	(0.021)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
R^2	0.421	0.518	0.580	0.717	0.809
ln(1− Personal MTR)	0.309***	0.328***	0.845***	1.200***	0.107
	(0.097)	(0.103)	(0.249)	(0.319)	(0.194)
ln(1− Personal MTR) × Agglom.	-0.194**	-0.286***	-0.423**	-0.667***	-0.030
	(0.086)	(0.086)	(0.171)	(0.238)	(0.054)
State Patents × ln(1− Personal MTR)	0.016*	0.007	-0.011	-0.021	0.021
	(0.009)	(0.010)	(0.022)	(0.034)	(0.019)
State Patents	0.031***	0.033***	0.090***	0.076**	0.027***
	(0.007)	(0.008)	(0.026)	(0.031)	(0.010)
ln(1− Corp. MTR)	0.043	0.040	-0.017	0.035	-0.037
	(0.057)	(0.053)	(0.101)	(0.193)	(0.124)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	6460412	6460412	4566398	4415498	1485493
Mean of Dep. Var.	0.707	0.422	0.458	2.779	0.500
S.D. of Dep. Var.	0.455	0.494	0.664	1.454	0.500
R^2	0.420	0.517	0.579	0.717	0.807

Notes: Table plots estimates of the interaction of agglomeration forces with tax rates. Regression is identical to 4, except that it includes a control for the total number of patents in the state, and interactions of the tax rate with both our agglomeration measure and the total number of patents in the state.

A.4 Case Studies

We present here three special episodes of tax reform in New York, Delaware, and Michigan to provide some sharp visual evidence of the effects of taxes on innovation. Figures A16-A17 show the results from each of these episodes. In each case, the black solid line represents the time series in the state under consideration, while the dashed line represents a control state. The control state is constructed according to the synthetic control method of Abadie et al. (2010). That is, it is a weighted average of other states in the sample, where the weights are chosen to best match the average innovation outcome of interest (patents, inventors, or citations), as well as real personal income per capita and population density for the period before the tax change in the state of interest.

For the case of New York, the control state turns out to be California. For Michigan and Delaware, it is a combination of other states. For the post-tax change period, the synthetic state represents a plausible counterfactual of what may have happened in the state of interest absent the tax change. The first panel shows log patents, the second shows log inventors and the third shows log citations. The dashed vertical lines (or, for Michigan the gray area) represents the timing of the tax change.

New York 1968 vs. California

The first case study is shown in Figure A16 and concerns New York's 1968 tax reform bill, in which the top marginal personal income tax rate increased from 10% to 14% and its state top corporate tax rate increased from 5.5% to 7%. The control state here is California, where the top tax rate increased as well from 7% to 10%, but remained lower while the corporate tax rate remained the same at 5.5%. All variables are normalized at their 1965 levels. Before the tax bill, New York and California follow remarkably similar trends for all three innovation outcomes. However, after the reform, they diverge and New York performs much worse in terms of innovation relative to the synthetic control.

Michigan 1967-1968

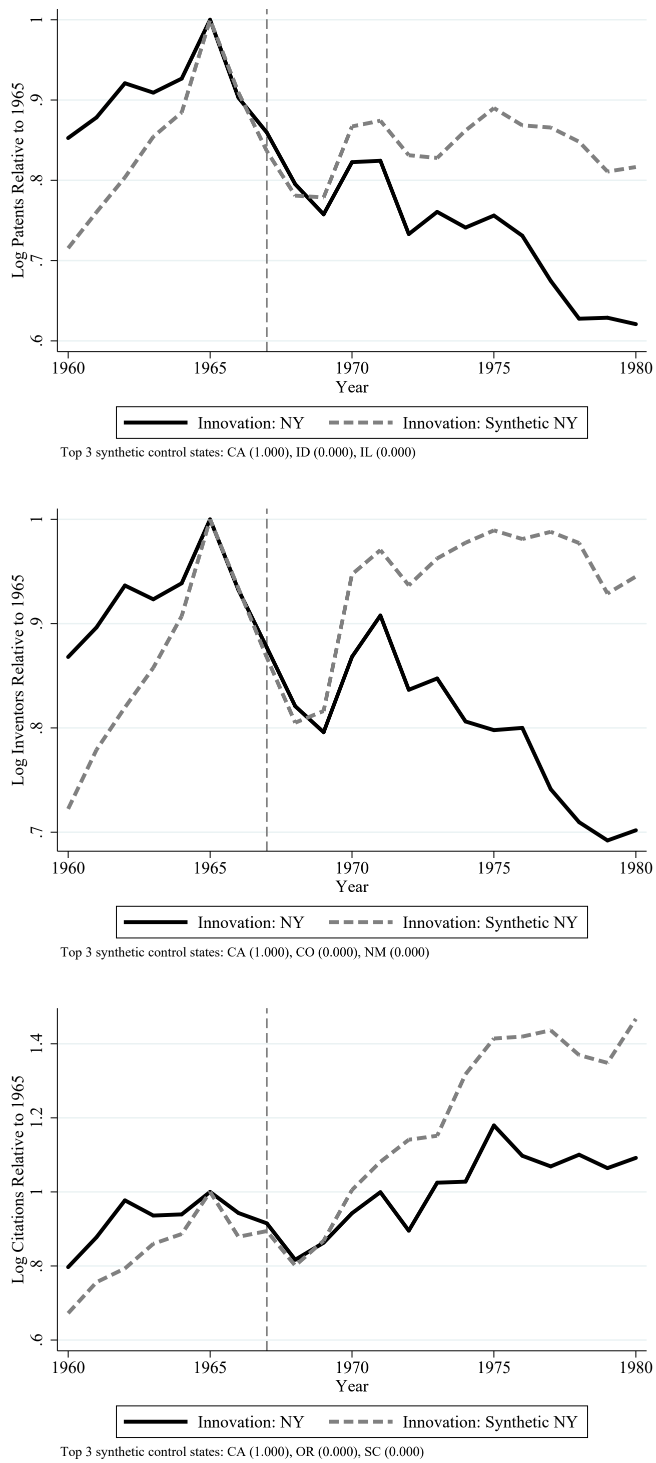
Figure A17 shows the case study of Michigan. Michigan introduced its personal state tax rate in 1967 at 2.6%. One year later, in 1968, it introduced its corporate state tax at 5.6%. The synthetic control for Michigan is composed of several variations on California, Ohio/Pennsylvania, and, for some of the outcome variables, a bit of Texas. While the control state and Michigan evolve very similarly before 1967, Michigan starts performing significantly worse for the innovation outcome measures after the introduction of its tax regime.

Delaware 1969-1970

The third case study concerns Delaware. In July 1969, the corporate tax rate increased from 5% to 6%, and in August 1971 a temporary surcharge of 20% was added on top of the 6% corporate tax rate. In 1970, the personal tax rate increased from 11% to 18%. In this case, the best-fitting synthetic control is comprised of Nevada, California, and Connecticut. Figure A18 shows that the effects on patents, citations, and inventors were noticeably large with the negative trend setting in at the time of the tax reform.

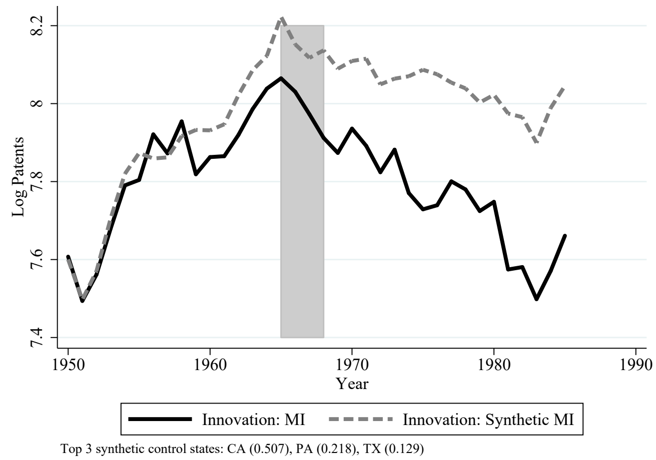
These case studies provide particularly clear visual evidence of a strong negative relationship between taxes and innovation. When combined with the macro state-level regressions, the instrumental variable approach and the border county analysis, the results overall bolster the conclusion that taxes were significantly negatively related to innovation outcomes at the state level.

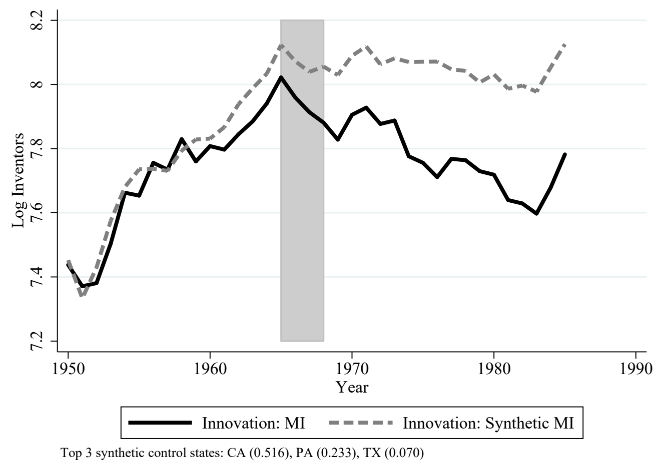
Figure A16: Synthetic Control Analysis: New York 1968

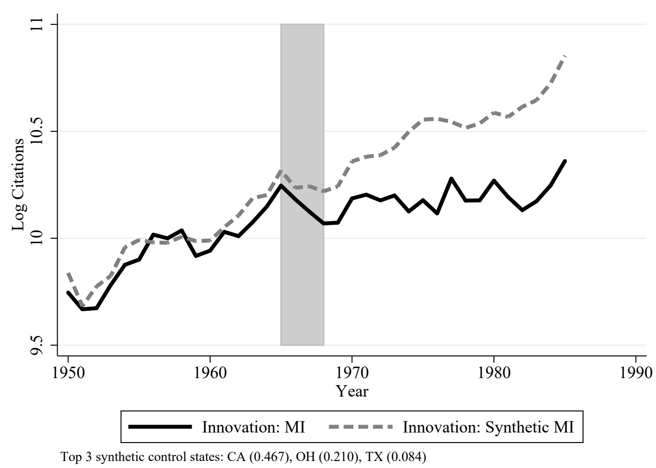


Notes: Figure plots synthetic control analyses for New York's 1968 tax reform bill, in which the top marginal personal income tax rate increased from 10% to 14%, and its state corporate tax rate increased from 5.5% to 7%. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations. We normalize the patent counts for synthetic and actual New York to be one in 1965.

Figure A17: Synthetic Control Analysis: Michigan 1967-68

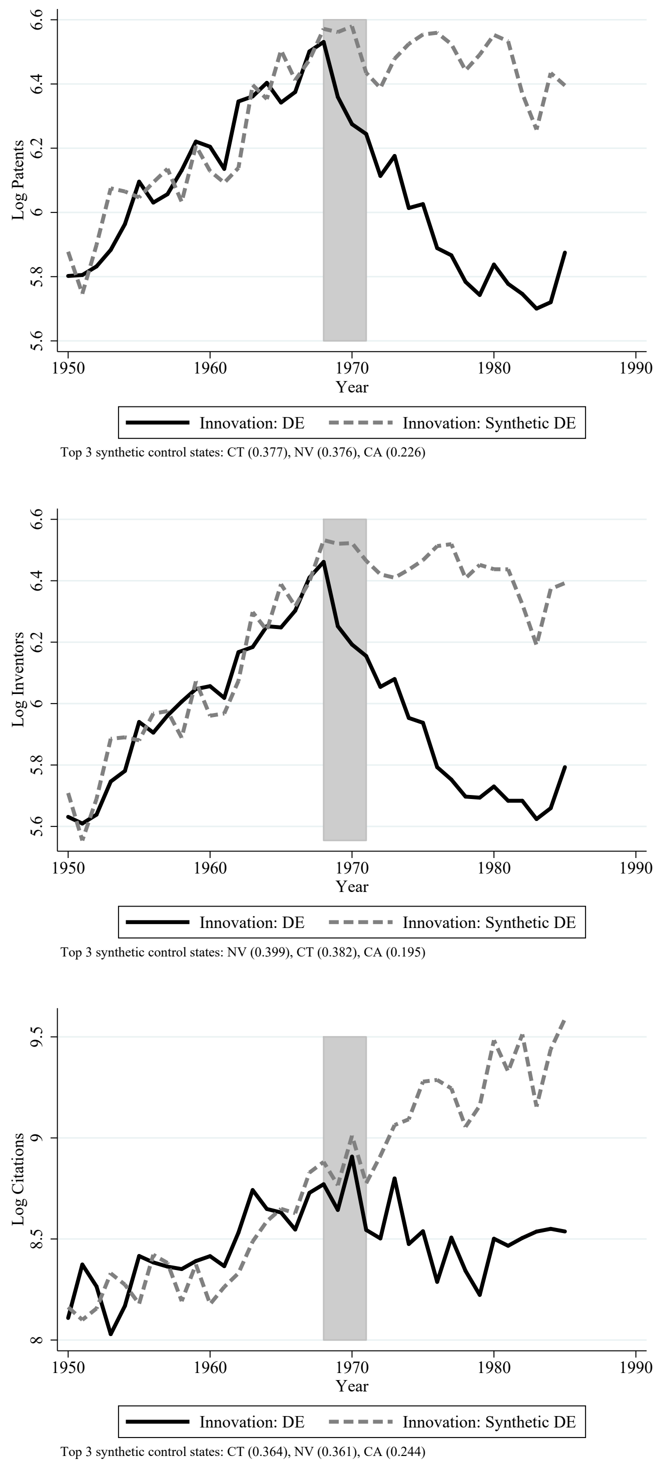






Notes: Figure plots synthetic control analyses Michigan around its major reforms in 1967 and 1968. In 1967, Michigan introduced its personal income tax, at a rate of 2.6%. In 1968, it then introduced its corporate income tax, at a rate of 5.6%. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations.

Figure A18: Synthetic Control Analysis: Delaware 1969-71



Notes: Figure plots synthetic control analyses around Delaware's tax reforms. In July 1969, the corporate tax rate increased from 5% to 6%, and in August 1971 a temporary surcharge of 20% was added on top of the 6% corporate tax rate. In 1970, the personal tax rate increased from 11% to 18%. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations.

ONLINE APPENDIX – NOT FOR PUBLICATION

for "The Effects of Taxes on Innovation: Evidence from Historical U.S. Patent Data"

by Ufuk Akcigit, John Grigsby, Tom Nicholas, and Stefanie Stantcheva

OA.1 Disambiguation Algorithm

We employ the algorithm of Lai et al. (2014) to disambiguate inventors in our historical patent data.[37] The goal of disambiguation is to determine if two patent-inventor level records were produced by the same inventor. A problem of this sort may be distilled into a clustering problem well-suited to standard machine learning algorithms: given a training dataset and a set of features – such as inventor name, location, technology class, assignee, and coauthor networks – we wish to group records together into profiles which indicate that the two records were produced by the same inventor. The goal is to assign probabilities of an inventor match based on the characteristics of every pair of observations. The central idea is that two records coming from two very similar names (not necessarily identical: "John A Smith" vs "John Adam Smith" for instance) working in similar subject areas, working for the same company in roughly the same geographic location, are likely to be the same person.

Such a machine learning approach has three central benefits relative to other more rudimentary approaches, such as treating each individual name as a separate inventor, or hand-matching innovators' records to one another. First, the Lai et al. approach permits minor name typos or data entry errors, without incorrectly decoupling these inventors. Second, it provides probabilistic matches based on more information than name and location, which helps disambiguate between common names – a John Smith working in software is likely different to a John Smith with patents in bootmaking. Finally, the algorithm does not impose any functional forms on the relationship between a pair's set of attributes and the probability that those pairs belong to the same inventor.

Of course, this machine learning approach is imperfect and will struggle to correctly match inventors who drastically change their names or have exceptional careers. For instance, if an inventor named Jane Smith changes her name after marrying a man with surname Robertson, the algorithm will struggle to adapt, as names are the most distinguishing piece of information amongst records. Similarly, if a software engineer living in California and working for Apple decides to change his career and move to Montana to open a new shoe factory, the algorithm is likely to suggest that these are two separate inventors, rather than one inventor with such an uncommon career trajectory.

The clustering exercise is subject to two principal challenges. First, one must produce a suitable

[37]The code and associated files for the original disambiguation may be downloaded from `https://github.com/funginstitute/downloads`; accessed October 13, 2016.

training dataset from which to glean the probability that two patent records with a similarity profile of x belong to the same inventor. Here, one may follow two approaches. One could submit a hand-curated dataset of known matches to the disambiguation algorithm to determine the likelihood of a match. However, the construction of these datasets are often subject to bias if, for example, researchers are more likely to include better-known inventors. An alternative approach, and the one followed by Lai et al., is to allow the algorithm to produce its own training dataset based on features in the data. For example, a training dataset of known matches could be constructed by examining individuals with matching rare names.

Our baseline approach lies somewhere in between these two strategies. We use the matches of Lai et al. to form the basis of our training dataset. We draw twenty million pairs of records belonging to different inventors according to Lai et al. to complete our training dataset. Using this as a training dataset relies on two principal assumptions: first, we assume that the Lai et al. disambiguation correctly identifies inventors, and second we assume that the sets of features that were predictive of inventor clustering are stable over time, so that the same rules for determining matches in the modern sample of Lai et al. will apply to our historical sample. We choose this approach in order to best match the state-of-the-art disambiguation of inventors in the modern data.[38]

The second major challenge to the disambiguation exercise is computational. Ideally, one would compare every pair of records in our data, and build a similarity profile for each. However, with over 12 million unique patent-inventor records in our dataset, one would have to compare over 144 trillion record pairs in order to compare each record to each other, which is computationally infeasible. To circumvent this challenge, we follow Lai et al. in disambiguating successively larger blocks. We first group records into blocks of possible matches, based on the first characters of an inventor's name. Then we compare all records within a block to one another, but never compare across blocks. After disambiguating a set of narrow blocks, we expand the size of the block, for example by considering all record pairs that match the first three letters of an inventor's name, rather than the first five letters. By iteratively allowing progressively larger blocks, and assuming clusters within prior blocking rounds were successfully disambiguated, we greatly reduce the computational burden of the disambiguation.

Our starting point is the historical inventor data digitized by Akcigit et al. (2017), combined with the patent data of Lai et al. (2014) available on the Harvard Dataverse Network (HDN).[39] We first manually clean inventor names and location to correct for obvious typos. The most common correction is to remove prefixes and suffixes, such as "DR," "JR," and "SR." In addition, we standardize names to be all capital letters, and consider a person's first name to be the first word of their name. Finally, we consider only the first patent class listed on a patent document to be

[38]In early versions of the paper, we experimented with allowing the algorithm to find its own training sets, and found qualitatively similar headline results.

[39]Accessed from https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15705 on February 13, 2017.

that patent's primary classification. If our OCR process generates missing information, such as a missing name, class or location, we supplement the data with patent data from patentsview and the NBER patent data to fill in information where possible. These auxiliary data sources only contain patents granted since 1975, and so cannot improve the dataset's early years. Dropping the 1970s from our analysis does not meaningfully affect our results.

To compare records, we construct a similarity profile for every pair of records to be compared. A similarity profile x is a vector of similarity scores for the active attributes in the disambiguation. Specifically, a similarity profile is encoded as follows:

- First and Last names
  1. If one of the two records is missing the name
  2. If there is no clear misspelling or abbreviation employed, and the strings do not exactly match
  3. If there is a misspelling (defined as either missing 1 or 2 characters somewhere, or switching the place of a few characters)
  4. If exact match or, in the case of first names, if one string appears to be an abbreviation of the other in that it has the first 3 characters the same (e.g. "ROB" and "ROBERT")
- Middle Names
  0. If have different middle names
  1. If one of the two records have missing middle name
  2. If both records have missing middle name
  3. If one record has a full middle name (e.g. "WILLIAM") and the other has just the middle initial which matches the full middle name (e.g. "W").
  4. If exactly the same name
- Location
  1. If over 50 miles apart
  2. If under 50 miles apart
  3. If under 25 miles apart
  4. If under 10 miles apart
  5. If under 1 mile apart
- Patent Classes
  0. If different strings
  1. If exactly the same string

- Assignees
  5. If the Jaro-Winkler string distance between assignee names is at least 0.9
  4. If JW distance > 0.8
  3. If JW distance > 0.7
  2. If one of the two records has a missing assignee
  1. Otherwise
- Coauthors
  1. If coauthors exactly the same (coauthors entered as <First Initial> . <Last Name> and separated by comma in the variable)
  0. Otherwise
- Country
  0. If different country
  1. If the same non-US country
  2. If the same US country

Next, one may construct, for every observed similarity profile, the probability that this profile belongs to the same inventor or not, by comparing the frequency with which it occurs in the training dataset. Specifically, defining $\mathcal{M}$ to be the set of matched inventor pairs in the training dataset, and $\mathcal{N}$ to be the set of non-matched inventor pairs in the training dataset, one may use Bayes' rule to write the probability of a match as

$$P(\mathcal{M}|x) = \frac{P(x|\mathcal{M})P(\mathcal{M})}{P(x|\mathcal{M})P(\mathcal{M}) + P(x|\mathcal{N})\left(1 - P(\mathcal{M})\right)}$$

where $P(\mathcal{M})$ is the prior probability of a match, which we follow Lai et al. in setting as proportional to the ratio of the number of within-cluster pairs (i.e. disambiguated inventors from prior blocking rounds) in a block to the total number of pairs in that block.[40] For numerical reasons, it is more convenient to work with the posterior *odds* of a match, defined as

$$\frac{P(\mathcal{M}|x)}{1 - P(\mathcal{M}|x)} = \frac{P(x|\mathcal{M})}{P(x|\mathcal{N})} \cdot \frac{P(\mathcal{M})}{1 - P(\mathcal{M})}$$

In particular, we calculate the likelihood ratio, $r(x)$, for every observed similarity profile x. This likelihood ratio is defined as

$$r(x) = \frac{P(x|\mathcal{M})}{P(x|\mathcal{N})} \tag{OA1}$$

[40]The discrete nature of the similarity profile space described above makes the computation of this match probability much simpler.

This can be determined directly from the training dataset by comparing the number of records with similarity profile x that belong in the matched training dataset (i.e. come from the same inventor), to the number of records with similarity profile x that belong in the unmatched training dataset (i.e. come from different inventors).[41] Once we have the likelihood ratios calculated, we invert them to calculate the probability that two records originated from the same inventor:

$$P(\mathcal{M}|x) = \frac{1}{1 + \frac{1-P(\mathcal{M})}{P(\mathcal{M})}\frac{1}{r(x)}} \tag{OA2}$$

We say that two records originated from the same inventor if this posterior probability of a match is at least 0.99.[42]

Our blocking routine proceeds as follows:[43]

Round 1. Block based on exact first and last name. Compare records based on middle name and patent location.

Round 2. Block based on exact first and last name. Compare records based on middle name, coauthor network, patent class, and assignee name.

Round 3. Block based on first five characters of first name, and exact last name. Compare records based on middle name, coauthor network, patent class, and assignee name.

Round 4. Block based on first three characters of first name, and exact last name. Compare records based on middle name, coauthor network, patent class, and assignee name.

Finally, we subset our data to only consider US inventors. As was indeed the case in our time period, the most productive inventors are Kia Silverbrook, Shunpei Yamazaki, George Lyon, Donald Weder, and Melvin De Groote. We refer the reader to Lai et al. (2014) for additional statistics on the performance of the algorithm on modern data.

OA.1 Disambiguation: Performance

This disambiguation procedure is subject to two types of error. The first, which we dub a Type I error, occurs when two records are linked together as if they were from the same inventor, but in reality was created by two distinct individuals. Such errors are most likely to occur from the "common name" problem, where multiple distinct individuals have the same name. This is particularly

[41] To account for small sample bias in rare similarity profiles, we follow Lai et al. in applying a Laplace correction to these likelihood ratio values.

[42] In the early stages of our analysis, we experimented with match thresholds of 0.98 and 0.95 to determine whether records originated from the same inventor. After examining the data by hand, we determined that this was too low, as common names such as Robert Smith were often spuriously considered the most prolific inventors in the data. This problem largely vanished with the threshold of 0.99.

[43] We experimented with additional rounds of blocking, as well as with allowing for inexact surname matches in the blocking routine. Manual checks of the data revealed that this routine minimized errors with common names, and correctly matched the most productive inventors as listed by outside data sources.

difficult if, for instance, parents gave eponymous names to their offspring. Another source of this problem arises from an inability to distinguish whether two records with the same name appear in multiple states in two subsequent years – it can be difficult to tell whether such records reflect one inventor who moves or two distinct inventors.

The second, a Type II error, occurs when two records fail to be linked together into one inventor ID despite being produced by the same inventor. These errors occur when the algorithm is too strict in its criteria for matching workers together. Increasing the threshold of similarity at which two records are considered the same inventor reduces the likelihood of Type I errors while increasing the probability of Type II errors.

We check the performance of the algorithm along these two dimensions as follows. To check Type I errors, we construct a dataset by considering records that share same first three letters of their last name. We consider the 8 most common first three letters: "SCH," "WIL," "HAR," "CHA," "SMI," "STE," "SIL," "JOH," "BRO." We then manually checked this dataset to determine the Type I error rate by comparing records' similarity profiles, as well as their application years (to remove the influence of eponymous parent-child pairs). The goal was to determine the share of patent $\times$ inventor records that were assigned the same inventor ID but appeared to belong to different people by human judgment. This process revealed that just 1.5% of records were incorrectly grouped into the same inventor ID, suggesting that the Type I error rate is low.

To check the prevalence of Type II errors, we consider the share of records with the same set of progressively comprehensive characteristics that are matched to the same inventor. Table OA1 reports these shares. Each row of the table reports the share of records with the same set of observable characteristics that have multiple inventor IDs. For instance, the first row reports the share of records which have the same name but multiple inventor IDs, while the second row shows the share of records that have the same name and same state, but multiple inventor IDs. As we progress down the table, the set of matching characteristics get more and more stringent - the final row reports the share of records which have the same name, class, assignee, year and city, but multiple record IDs. For the purposes of the discussion below, let us define two inventor IDs to be "part of an incorrect split" for a given set of characteristics if they share those same characteristics, but have different inventor IDs.

The four columns calculate this share in different ways. The first two columns consider inventor-weighted shares: that is, what share of inventor IDs are part of an incorrect split? The second two columns consider patent-weighted shares: what share of patents belong to inventor IDs that are part of an incorrect split? Columns 1 and 3 count all inventor IDs that are part of an incorrect split in the numerator of this share. That is, if there are three inventors IDs with the same set of characteristics, all three will count as being part of an incorrect split. This calculation somewhat overweights the set of incorrect splits. For instance, suppose that there are two inventors, labeled A and B, that have the same name and location. Inventor A has 1,000 patents, while inventor B only has one. One might reasonably claim that only inventor B's one patent record was incorrectly disambiguated. To account for this, columns 2 and 4 remove the inventor ID with the most patents

Table OA1: Disambiguation Performance: Type II errors

		Inventor-Weighted		Patent-Weighted	
		With Duplicates	No Duplicates	With Duplicates	No Duplicates
Criteria	**Location Match**	(1)	(2)	(3)	(4)
Name Only	No Location	34.7	11.4	22.4	9.6
	State	22.9	9.2	15.0	5.4
	County	12.5	5.4	8.2	2.8
	City	9.2	4.1	6.1	2.0
Name + Class	No Location	9.6	4.2	5.9	2.0
	State	7.0	3.2	4.4	1.5
	County	4.2	1.9	2.6	0.84
	City	3.0	1.4	1.9	0.60
Name + Assignee	No Location	11.4	4.9	6.9	2.4
	State	6.6	3.0	4.2	1.3
	County	2.4	1.2	1.6	0.50
	City	0.07	0.03	0.05	0.01
Name + Class + Assignee	No Location	3.3	1.6	2.0	0.64
	State	2.2	1.0	1.4	0.42
	County	0.80	0.39	0.52	0.16
	City	0.02	0.01	0.01	0.00
Name + Class + Assignee + Year	No Location	0.65	0.32	0.35	0.11
	State	0.45	0.22	0.25	0.08
	County	0.15	0.08	0.08	0.03
	City	0.00	0.00	0.00	0.00

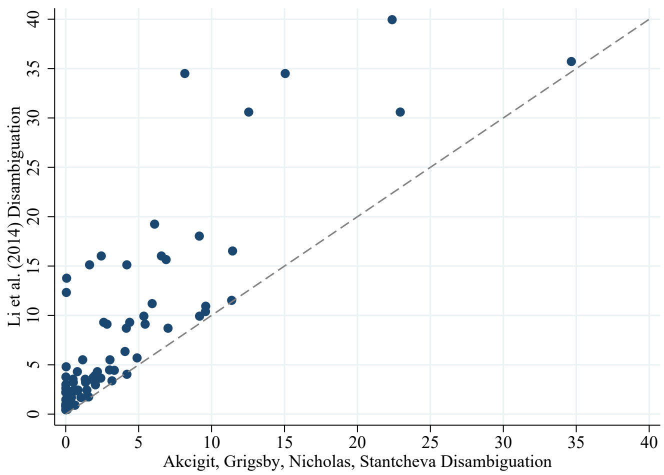
Notes: Table reports the share of potential type II errors by a variety of criteria. The table shows the share of observations that have the same sets of a given set of criteria, but multiple different inventor IDs in our disambiguated patent data. Each row corresponds to a different set of criteria; for instance, the top row considers the share of records with the same name that have different inventor IDs. Each column represents a different method of counting identical records. Columns (1) and (2) consider the share of inventor IDs which are part of a duplicate pair, while columns (3) and (4) consider the share of patents that are part of a duplicate pair. Columns (2) and (4) only consider the inventor ID with the fewest patents to be incorrectly matched, while columns (1) and (3) consider both inventor IDs with the same values of the criteria to be matched.

within a set of criterion from the set of incorrectly split IDs.

The table shows that 34.7% of inventor IDs have another inventor ID with the same name. These inventors account for 22.4% of patents. However, only 7% of inventors have the same name, class and state as another inventor ID (accounting for 4.4% of patents). Removing the most prolific inventor from the set of incorrectly split inventors reveals that only 3.2% of inventor IDs (accounting for 1.5% of patents) were split from another inventor with the same state, name and patent class.

These numbers are small and are unlikely to meaningfully bias our core results. By way of comparison, Figure OA1 compares the numbers of Table OA1 with analogous numbers calculated using the Lai et al. (2014) dataset. The horizontal axis plots the rate of incorrect splitting in our data, while the vertical axis plots it in the Lai et al. data. The dashed line is a 45-degree

Figure OA1: Type II Error Comparison – Harvard Dataverse NetworkLai et al. (2014) comparison with our disambiguation



Notes: Figure plots the rate of Type II errors in our disambiguation and in the Lai et al. (2014) data. Each dot is a cell from Table OA1; see notes from that Table for details.

line, while each dot is a different set of characteristics and method of calculating the share of split inventors; that is, each dot represents a cell of Table OA1. The fact that every dot is above the 45-degree line indicates that our disambiguation has fewer Type II errors than the disambiguation of Lai et al. (2014) by every method used to calculate it. We consider this to be evidence that our disambiguation performs admirable, particularly coupled with the low Type I error rate of 1.5%.[44]

Comparison with External List of Prolific Inventors. In this section, we assess our disambiguation algorithm's performance on the most prolific US inventors. We compare the list of prolific inventors available from Wikipedia[45] to the number of patents of these inventors according to our disambiguation algorithm.

The first step of this exercise is to identify the inventors from our disambiguated dataset that correspond to the ones listed in Wikipedia. To do so, we match each of Wikipedia's inventors to a set of inventors in our dataset with the same first and last name. We then keep only inventors from our dataset that have either a missing middle name or a middle name starting with the same letter of the Wikipedia's counterpart. Subsequently, we choose the unique inventor ID in each set with total number of patents closest to Wikipedia's. Results are robust to choosing simply the most patented inventor per set. Then, we compute the percentage deviation of total patents of

[44] We also considered allowing inventors to have the same name if one inventor's name was a common nickname of another. A list of common English nicknames was obtained from `https://www.familiesunearthed.com/nicknames.htm`. Accounting for nicknames in this way had minimal impact on these tests, increasing the error rate by no more than 1% by any measure.

[45] Accessed from `https://en.wikipedia.org/wiki/List_of_prolific_inventors` on January 15, 2021. The source of the data from the Wikipedia table is mainly `http://patft.uspto.gov/netahtml/PTO/index.html`, or Google patents

such inventors relative to Wikipedia's and we classify the results in different intervals.

It is important to note that our dataset includes only patents that were granted between 1920 and 2010, whereas most Wikipedia's inventors were still active in the decade 2010-2020. To account for this, we first drop the few inventors who were active before 1920 for the bulk of their careers, such as Thomas Edison (1847-1931). Then, we consider different baskets of inventors depending on what percentage of their career is covered in the timeframe of our dataset (1920-2010). For instance, if we enforce that we observe at least 50% of an inventor's career, then we would include an inventor whose period of activity was 2000-2020, but not if it was 2001-2020.

The results are presented in Table OA2. The total number of patents of the most prolific inventors are generally underestimated in our dataset. However, this is mainly due to the mismatch in the coverage period. When we condition on observing at least 70% of an inventor's career span, our deviation from Wikipedia's patent counts is no larger than 5% for 55% of our inventors. Enforcing that we observe the entirety of an inventor's career increases this share to 75%.

Of course, there is no guarantee that the crowd-sourced Wikipedia list is perfectly accurate. It may additionally include patents for inventors who live abroad, while our data only covers inventors while they live in the US. Nevertheless, the fact that our disambiguated data produces patent counts which are close to those in Wikipedia is heartening. This, coupled with the relatively low rates of Type I and II errors uncovered above, gives us confidence that our disambiguated data are of a high quality.

OA.2 Assigning Inventors to States

Our patent data provides information on the residence address of the patent's inventors. However, we do not observe the residence of all inventors on a patent in the historical period. Specifically, we observe an inventor's state if either 1) they are the first inventor on the patent, or 2) the patent is contained in the Harvard Dataverse Network (HDN) data produced by Lai et al. (2014). In order to run our inventor-level regressions, we must assign each inventor to a particular home state. In this section, we detail our approach to doing so.

For all non-primary authors on historical patents, we impute a location using the following algorithm:

1. We assign all HDN and first author inventors to the state listed in the data

2. If an inventor is an HDN or first author inventor on one patent in a given year, but not on another patent, we assign that inventor to his first-author state. If he is first author in multiple states in that year, we assign him to the state listed on the patent if that state matches one of his first author states; otherwise we proceed to step 3 below (using alternative years)

3. We replace the inventor's state with the preceding year's state if state information is still missing.

Table OA2: Comparison of Wikipedia Patent Counts and Disambiguated Patent Counts for Prolific Inventors

Patent Count: Ratio of Our Disambiguation to Wikipedia	Threshold of Career Overlap					
	50%	60%	70%	80%	90%	100%
	(1)	(2)	(3)	(4)	(5)	(6)
1.05+	11	11	8	6	5	2
	(12%)	(17%)	(21%)	(29%)	(52%)	(25%)
1.01 – 1.05	8	8	8	5	1	1
	(9%)	(13%)	(21%)	(24%)	(8%)	(13%)
0.99 – 1.01	15	11	7	5	3	3
	(16%)	(17%)	(18%)	(24%)	(25%)	(38%)
0.95 – 0.99	17	12	6	3	3	2
	(19%)	(19%)	(16%)	(14%)	(25%)	(25%)
0.90 – 0.95	14	4	1	0	0	0
	(15%)	(6%)	(3%)	(0%)	(0%)	(0%)
0.75 – 0.90	16	11	5	1	0	0
	(18%)	(17%)	(13%)	(5%)	(0%)	(0%)
0.5 – 0.75	6	5	1	1	0	0
	(7%)	(8%)	(3%)	(5%)	(0%)	(0%)
0 – 0.5	4	2	2	0	0	0
	(4%)	(3%)	(5%)	(0%)	(0%)	(0%)
Total	**91**	**64**	**38**	**21**	**12**	**8**
	(100%)	**(100%)**	**(100%)**	**(100%)**	**(100%)**	**(100%)**

Notes: Table compares the patent counts of inventors in our disambiguation with those taken from an external Wikipedia data source. Each row reports the number of inventors with a particular number of patents in our disambiguation relative to the Wikipedia data. For instance, the row 1.05+ reports the number of inventors who have at least 5% more patents in our data than reported in the Wikipedia table. Each column segments the sample to inventors for whom we observe at least X% of their career in our data, which spans 1920-2010. The counts of inventors in each cell are reported in each row, with the percentage of inventors reported in parentheses beneath the counts.

4. We replace the inventor's state with the following year's state if state information is still missing.

5. If the inventor-patent record is still missing state information, but the inventor has multiple first-author states listed in that year, then we pick a random first-author state for that inventor-patent.

6. If all else fails, we assign the state of the first-author on the patent.

An additional challenge arises from the fact that a number of inventors have patents granted in multiple states in the same year. There may be many causes for multiple unique states within a given year for an inventor. The most common causes of these multi-state inventors are:

- An inventor may live in state A until midway through a particular year, and then move to state B. They file a patent application both in state A before moving and in state B after moving. They never file a patent in state B before moving, and never file a patent in state A after moving.

- Inventors may have multiple home addresses. As a result, they consistently file in both state A and state B in multiple years. For example, inventors may spend half of the year in Chicago, IL, and half of the year in Milwaukee, WI, and thus frequently have patents in both of these states in a given year.

- Inventors have multiple coauthors, who live in different states and who alternate in terms of who is the first listed author. For instance, Harvey Clayton Rentschler lives in Pittsburgh, PA, but frequently coauthors with J. Marden, who lives in Orange, NJ. Every time they coauthor a patent, the location is listed as Orange, NJ, but every time Harvey Rentschler sole authors a patent, his location appears to be Pittsburgh. These situations are particularly common among assigned patents, and seem to account for all individuals living in an exceptionally high number of states. Indeed, everyone who shows up in 7 or more states has a coauthor on their patents, while the share of those with a coauthor is 92.8% for those with multiple states, compared with just 66.3% for those in one state[46]

- Possible disambiguation errors: two individuals may have very similar names, work in similar classes, and live just across a state border from one another (so are close in latitude-longitude). As a result these two separate inventors may be classified as the same person by the disambiguator. This would inflate the number of states an individual lives in.

To address this concern, we assign multi-state inventors a home state using the following algorithm:

1. Each year, assign an inventor to the modal state in which we observe him/her operating as a sole author.

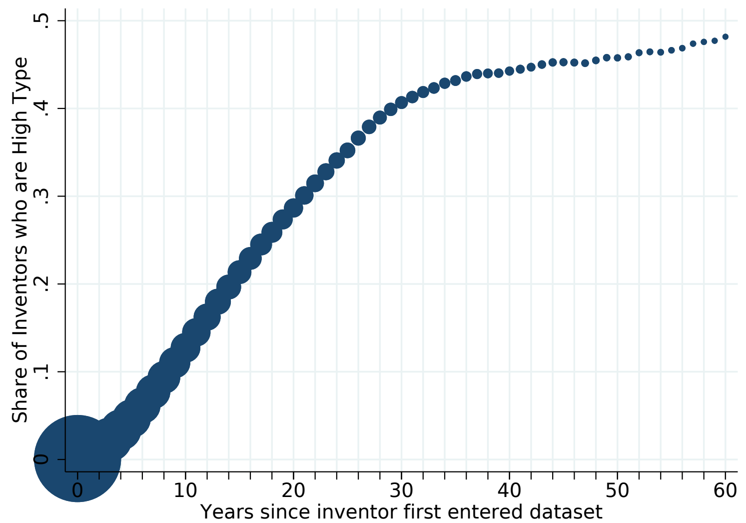
2. If the inventor does not have any sole authorships in that particular year, check if they have sole authorships in the preceding or subsequent year. If the preceding and subsequent year both have sole authorships in the same modal location, then assign the inventor to that state. This smoothes over off years for inventors and removes spurious migration.

3. If we still do not have a location for the inventor, then we assign them to the modal location we observe them in in the given year, regardless of whether the patent was sole authored or coauthored.

4. If the inventor has two modal states (e.g. has 2 patents in both Illinois and Wisconsin in the given year), then choose a random choice of those states and assign the inventor to that state.

[46]This is partially mechanical as these inventors are also more productive so have more chances to appear in multiple states.

Figure OA2: The Relationship Between Inventor Quality and Tenure



Notes: This figure plots the share of inventors who are counted as high quality in a particular year against their tenure in the dataset. Inventors are defined as high quality if they are in the top 10% of career patent counts up through the year in question. The size of each marker reflects the share of inventors in that tenure bin.

OA.3 Tenure versus quality

One might be concerned that our quality measures simply reflect career length. Those with longer careers are likely to have accumulated more patents, regardless of their underlying productivity. For our purposes, it suffices that those with more patents are more likely to be in the top ten percent of the income distribution, so a correlation between career length and quality measures would not invalidate our empirical approach. In addition, we control for a quadratic in inventor tenure, as well as an indicator for being high quality, in our regressions. Nevertheless, it is useful to explore the relationship between inventor quality and tenure in the dataset.

Figure OA2 plots the relationship between inventor quality and tenure. The horizontal axis measures an inventor's tenure in the dataset, defined as the number of years since the inventor first applied for a patent. The vertical axis plots the share of inventors with that tenure level who are counted as high type under our baseline measure of quality; that is, the share of inventors who are in the top ten percent of the distribution of patents accumulated in ones career up through that year. The size of the markers is proportional to the share of observations in the dataset who have a given tenure level.

Unsurprisingly, the figure shows a strong positive correlation between quality and tenure. However, it is not the case that high quality inventors are only those with high tenure. Approximately ten percent of inventors with 10 years of tenure are high quality. This number rises to 28% when considering 20-year inventors. Even at very high tenure levels (of which there are very few), no more than 45% of inventors are counted as high quality. Thus the relationship between tenure and quality, while significant, is far from one-for-one.

OA.4 Citation Adjustment

Our data includes the full network of citations from patents granted from September 1947, when the USPTO began to note citation data in a systematic way, to 2015. Citations start in 1947 because a USPTO Notice was issued on December 19th, 1946, instructing examiners to add citations in the published format of the patent, a practice that was incorporated into the *Manual of Patenting Examining Procedure* (paragraph 1302.12).

For patents granted before 1947, the noted citation count is left censored: a patent granted in 1940 will only have citations from patents granted after 1947, but will not have citations from patents between 1941 and 1946. This artificially deflates the number of citations received by patents before 1947, confounding attempts to use citations as an objective measure of a patent's quality. Furthermore, aggregate citation trends may weaken the link between raw citation counts and patent quality. For instance, if patents granted in 1960 cite an average of 5 prior patents, but those granted in 1990 cite 20 patents, one might expect the average citation received from a 1960 patent to be more indicative of a high quality innovation than a citation received in 1990. We therefore adjust the number of citations received by each patent following the quasi-structural approach laid out in Hall et al. (2001).

This approach relies on two critical assumptions. First, we assume that the citation process is *stationary*. That is, we assume that the evolution of citation shares does not change over time: a patent will on average receive a share $\pi_{k\tau}$ of its citations τ years after it is granted, regardless of the grant year. This allows us to project back our adjustment factors to patents filed before the citation data began in 1947. Second, we assume *proportionality*. That is, we assume that the shape of the citation evolution does not depend on the total number of citations received so that highly cited patents are more highly cited at all lags. This allows the application of the same adjustment factor to every patent in our data granted in a given period and belonging to a given patent class.

The adjustment proceeds as follows. We start with the full patent citation network data, keeping only those patents granted in the United States. Let C_{kst} be the total number of citations to patents in year s and technology category k coming from patents in year t.[47] Further, define P_{ks} to be the total number of citations received by patents granted in year s in technological category k. One can then define $\pi_{kst} = C_{kst}/P_{ks}$ to be the average share of citations received by patents in class k in year s from patents granted in year t We assume that π_{kst} is some multiplicatively separable function of grant year, patent category, and a citation lag. That is, we can write

$$\log[\pi_{kst}] = \alpha_0 + \alpha_s + \alpha_t + \alpha_k + f_k(L) \qquad \text{(OA3)}$$

[47] For the purposes of the adjustment, we use technological categories as defined by the NBER patent data. For a detailed description of these data, see Hall et al. (2001).

for $L = t - s$ the lag between cited and citing patent grant years, and $f_k(\cdot)$ some category-specific function of these lags. For our purposes, we define $f_k(L) = \tilde{\gamma}_{k,L}$. We may then estimate equation OA3 using OLS to recover estimates of $\alpha_0, \alpha_s, \alpha_t, \alpha_k$, and $\tilde{\gamma}_{k,L}$ for each value of s, t, k and L in our data.[48] Taking exponentials of equation OA3 yields

$$C_{kst}/P_{ks} = e^{\alpha_0} e^{\alpha_s} e^{\alpha_t} e^{\alpha_k} e^{\tilde{\gamma}_{k,(t-s)}} \tag{OA4}$$

This formulation allows us to standardize citation counts over time and across categories. Specifically, in order to adjust for patent class, cited year, and citing year effects, we weight each citation from a patent in year t to a patent in class k in year s by $\exp(-\hat{\alpha}_k - \hat{\alpha}_s - \hat{\alpha}_t)$. Each patent's citation counts are therefore reflective of the patent's quality relative to the average patent in some base year and category.[49]

While this procedure accounts for aggregate differences across patent classes and grant years, it does not yet correct for bias arising from the left truncation of citation records. To build intuition for the truncation correction, consider an example in which each of the estimated α coefficients were 0: the only bias in our citation data arises from the lag. In that case, the assumptions of proportionality and stationarity suggest a natural adjustment factor for a patent granted L years before the 1947 cutoff. Define $G_k(L)$ to be the CDF of the lag distribution: the share of an average patent's citations received within the first L years after its grant. The adjustment factor is then given by

$$\sigma_{k,L} = \frac{1}{1 - G_k(L)}$$

We would then predict that a patent in category k granted in year $1947 - L$ and receiving c citations from patents granted after 1947 would have received $\sigma_{k,L}c$ citations had the USPTO kept track of citations before 1947.[50]

In order to incorporate the year and category fixed effects into this truncation adjustment framework, one must establish a notion of the CDF of the lag distribution conditional on year and category effects. To do so, we interpret the $\exp(\tilde{\gamma}_{k,L})$'s as weights for each patent in the citation data. For instance, if the estimated $\exp(\tilde{\gamma}_{k,L=2})$ is 2, then an average patent is twice as likely to receive a citation after 1 year than in the year of patent grant, conditional on year and category effects. To construct the CDF of citations by lag conditional on year and class effects, we can sum our estimates of $\exp(\tilde{\gamma}_{k,L})$, normalizing the estimated coefficients so that they sum to 1. This gives

[48] It is rare for a patent to receive citations more than 30 years after its initial grant date, and thus we top-code the citation lag L to have a maximum value of 30. That is, we define $L = \min\{t - s, 30\}$.

[49] For our purposes, we choose each patent citation to be relative to a patent in the "Other" category granted in 1975, receiving citations from patents also granted in 1975. Mechanically, this corresponds to setting the omitted categories in estimation of equation OA3 to be $k =$ "Other", $s = t = 1975$.

[50] Ignoring year and category effects and adjusting citations in this way does not significantly change the results presented in the main body of the paper.

us our estimate of $G_k(L)$:

$$\hat{G}_k(L) = \frac{\sum_{l=1}^{L} \exp(\tilde{\gamma}_{k,l})}{\sum_{l=1}^{30} \exp(\tilde{\gamma}_{k,l})} \tag{OA5}$$

We can then calculate our truncation adjustment factor as before[51]

$$\hat{\sigma}_{k,L} = \frac{1}{1 - \hat{G}_k(L)}. \tag{OA6}$$

To summarize, the citation adjustment proceeds in four steps:

1. Estimate equation (OA3) using OLS to recover $\alpha_0, \alpha_k, \alpha_t, \alpha_s$ and $\gamma_{k,L}$.

2. For each citation made from a patent p' granted in year t to a patent p in class k granted in year s is weighted by

$$\omega_{k,s,t} = e^{-\alpha_k - \alpha_t - \alpha_s}$$

   Define, for each cited patent p, the year- and category-adjusted citation count c to be the sum of the $\omega_{k,s,t}$ it received.

3. Calculate $\hat{G}_k(L)$ according to equation (OA5)

4. Using $\hat{G}_k(L)$, calculate the truncation adjustment factor $\hat{\sigma}_{k,L}$ according to (OA6). Finally, define a patent p's adjusted citation count to be $\tilde{c} = c \cdot \sigma_{k,L}$ if p is in class k and was granted L years before 1947.

OA.5 Historical Corporate Tax Data

We collected the corporate tax rates from a large variety of sources. We also collect surtaxes or surcharges, as well as additional temporary taxes imposed on top of the main rates. They are sometimes imposed as a percentage of regular tax liabilities and sometimes as a rate to add to the main rate. We record them as rates to add to the main rate with applicable thresholds. We have not collected minimum taxes (they are very low and probably not applicable to the companies in our sample) and alternative minimum taxes.

OA.1 Tax Rates

Historical data on the state corporate tax rates were collected from a number of sources. In particular, our tax rate data come from:

[51] Note that we only calculate the truncation adjustment up to $L = 20$, despite estimating $\gamma_{k,L}$ for L as large as 30. This is to bound $\hat{G}_k(L)$ away from 1, so that we do not divide by 0 in the adjustment. For L larger than 20, we apply the adjustment factor for $L = 20$.

- HeinOnline Session Laws. This is an archive of state legislation enacted since U.S. territories were established and provides great historical coverage.
- ProQuest Congressional. It supplements to HeinOnline's database for the District of Columbia.
- HeinOnline State Statutes. This is an archive of historical state statutes. In the early 20th century, state statutes were periodically recodified into clean statutes. Between these recodifications, publishers released annotations that recorded updates. HeinOnline contains statutes and annotations, mostly prior to 1940.
- State Tax Review and State Tax Handbooks by the Commerce Clearinghouse (CCH). The Commerce Clearing House is a company that publishes tax guides as a resource for businesses and tax professionals. We located their products through University of Michigan and the Library of Congress.
- Council of State Governments Book of States. These are a biannual publication aiming to review state-level tax changes. The first usable volume was published in 1948. In particular, the state finances chapter summarizes income tax developments and includes a chart for corporate income tax rates.
- Tax Foundation Publications.
- Report of the Subcommittee on State Taxation of Interstate Commerce (1964), also referred as *"The Willis Commission Report "*.
- State Income Tax Administration by Penniman and Heller. It was published in 1959 and provides a good overview of the development of corporate income taxes in US states.
- National Tax Association Proceedings.
- The Progress of State Income Taxation Since 1911, Lutz (1920).

OA.2 Tax Base Rules

Following Suárez Serrato and Zidar (2018), we use fifteen variables to control for changes in how the state corporate tax base is computed. Specifically, the variables used are:

- *Investment Tax Credit:* investment tax credit rate for a given state-year;
- *R&D Tax Credit:* statutory credit rate adjusted for recapture and type of credit for a given state-year;
- *R&D Tax Credit Base - Incremental Moving Average:* an indicator variable equal to one if the R&D tax credit applies to an incremental base that is a moving average of past expenditures in a given state-year;

- *R&D Tax Credit Base - Incremental Fixed Period* indicator variable equal to one if the R&D tax credit applies to an incremental base that is fixed on a level of past expenditures in a given state-year;
- *Loss carryback rules:* the number of years a corporation may carry back any excess loss following the loss year;
- *Loss carryforward rules:* the number of years a corporation may carry forward any excess loss following the loss year;
- *Franchise tax:* indicator variable equal to one if a Franchise tax is levied on corporations in a given state-year;
- *Throwback rules:* indicator variable equal to one if the state eliminates "nowhere income" that would be untaxed by either the state with the corporation's nexus or the state in which the relevant sales were being made;
- *Combined Reporting Rules:* an indicator variable equal to one if a state requires a unitary business to submit combined reporting;
- *Federal Income Tax Deductible:* indicator variable equal to one if the federal income tax is deductible in a given state-year;
- *Federal Income as State Tax Base:* indicator variable equal to one if the federal income tax base is used as the state tax base in a given state-year;
- *Federal Accelerated Depreciation:* variable equal to one if the federal accelerated depreciation is allowed in a given state-year;
- *Accelerated Cost Recovery System (ACRS) Depreciation:* indicator variable equal to one if the accelerated cost recovery system is allowed in a given state-year;
- *Federal Bonus Depreciation:* indicator variable equal to one if the federal bonus depreciation is allowed in a given state-year;
- *Sales Apportionment Weight:* the share of national profits of multi-state firms that are allocated to sales (for tax purposes) in a given state.

The loss carryback rule, the loss carry forward rule, the federal income tax deducibility, the federal income as state tax base, the federal accelerated depreciation, the federal bonus depreciation from 1958 through 1980 are collected from the State Tax Handbooks published by the Commerce Clearing House (CCH). From 1980 through 2010, these same variables are supplemented by Suárez Serrato and Zidar (2018). The investment tax credit data from 1964 onward are supplemented by Chirinko and Wilson (2008). The Federal R&D Tax Credit was introduced for the first time in 1981; one year later, in 1982, Minnesota was the first state to follow suit and enact a state R&D tax credit. Hence, data for state-level R&D Tax Credits (both the rate and whether the tax credit base is incremental with a moving average or incremental with fixed base) from 1982 onward come from Suárez Serrato and Zidar (2018).

The apportionment weights are compiled from a variety of sources. These sources include:

- The Progress of State Income Taxation Since 1911, Lutz (1920).
- Report of the Subcommittee on State Taxation of Interstate Commerce (1964), also referred as *"The Willis Commission Report "*.
- Hearings Before the Committee on the Judiciary, United States Senate, Ninety-fifth Congress, First and Second Sessions on Interstate Taxation (1977-1978).
- Report of the Committee of independent experts on company taxation, also referred as the Ruding Report.
- "Supplement to the Appendix to the Journal of the Senate Legislature of the State of California" (1951).
- CSG Book of the States.
- CCH State Tax Reviews and CCH State Tax Handbooks.

Again, data from 1980 onward are supplemented from Suárez Serrato and Zidar (2018). Since we lack exact data for each state-year, especially for the earliest period, we have to interpolate some years of the data. In particular, we assume that an apportionment rule is in place until we have explicit confirmation that the rule has changed.

While most states apportion based solely on the location of payroll, property, or sales, some states occasionally used concepts such as production costs. When states offer different apportionment rules to manufacturing versus service sectors, we use the manufacturing rules since most innovation occurred within the manufacturing sector in the latter half of the 20th century.

To construct our index "corporate tax base breadth," we follow Suárez Serrato and Zidar (2018) in constructing an index of the "corporate tax base breadth." We regress state corporate tax revenues as a share of GDP on all tax base and apportionment variables, as well as state and year fixed effects. That is, we estimate regressions of the form

$$\left(\frac{Revenue}{GDP}\right)_{st} = \alpha_s + \phi_t + \gamma \text{Corp. MTR}_{st} + \mathbf{X}'_{st}\mathbf{\Psi}^{BASE}_{st} + u_{st}$$

where $\left(\frac{Revenue}{GDP}\right)_{st}$ is the ratio of state corporate tax revenues to state GDP, α_s and γ_t, Corp. MTR_{st} is the state's top corporate tax rate, u_{st} is an error term and $\mathbf{X}_{st}$ is a vector of corporate tax base rules. Specifically, $\mathbf{X}$ contains R&D tax credits, the sales apportionment weight, years of allowable loss carryback and carryforward, and indicators for whether R&D tax credits are applied on an incremental base that is a moving average or fixed on a level of past expenditures, whether the state tax is a franchise tax, whether federal income taxes are deductible from income, whether the federal income tax base is used for state taxation, whether the state allows federal accelerated depreciation, whether the state has throwback rules, whether the state uses combined reporting rules, and state investment tax credits. We have state revenue data from 1980-2010, and we weight the regressions by each state's average GDP over the sample.

The index is the predicted value from this regression (excluding state and year fixed effects), standardized to have zero mean and unit standard deviation. Formally, we begin by defining a raw base index given by

$$\tilde{b}_{st} = \gamma \text{Corp. MTR}_{st} + \mathbf{X}'_{st}\mathbf{\Psi}^{BASE}_{st}$$

Then we standardize this raw index to have zero mean and unit standard deviation over the full sample. Define $\sigma_{\tilde{b}}$ to be the standard deviation of $\tilde{b}$ over the period 1958-2000 when we observe the state base rules. Letting S be the number of states in our sample, and T the number of years between 1958 and 2000, our final base index is defined as

$$b_{st} = \frac{\frac{1}{ST}\sum\limits_{s,t}\tilde{b}_{st}}{\sigma_{\tilde{b}}}$$

This index may be interpreted as the number of standard deviations higher revenue a state might expect to receive from its tax base rules, relative to an average state-year. Since the state documents containing tax base information are missing for 1979, we linearly interpolate our tax base index over this year.