TAXATION AND INNOVATION IN THE TWENTIETH CENTURY*

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This article studies the effect of corporate and personal taxes on innovation in the United States over the twentieth century. We build a panel of the universe of inventors who patented since 1920, and a historical state-level corporate tax database with corporate tax rates and tax base information, which we link to existing data on state-level personal income taxes and other economic outcomes. Our analysis focuses on the effect of personal and corporate income taxes on individual inventors (the micro level) and on states (the macro level), considering the quantity and quality of innovation, its location, and the share produced by the corporate rather than the noncorporate sector. We propose several identification strategies, all of which yield consistent results. We find that higher taxes negatively affect the quantity and the location of innovation, but not average innovation quality. The state-level elasticities to taxes are large and consistent with the aggregation of the individual-level responses of innovation produced and cross-state mobility. Corporate taxes tend to especially affect corporate inventors' innovation production and cross-state mobility. Personal income taxes significantly affect the quantity of innovation overall and the mobility of inventors. *JEL Codes:* H24, H25, H31, J61, O31, O32, O33

> *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.*
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> —Joseph Schumpeter, *Capitalism, Socialism, and Democracy* (1942), 198

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I. 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 effects 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 article, we bridge the data gap and provide new evidence on the effects 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 data sets, two of which are newly constructed. First, we assemble a panel data set 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 data set 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 (2006). 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 noncorporate 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 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 ("noncorporate") operating outside the boundaries of firms, as they face divergent incentives and may have distinct motivations. Also, the effects of corporate tax on individual inventors are the result of a complex chain of effects, including how taxes affect corporate income and firms' 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 effect 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 (IV) 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 flexibly we allow for time-varying state controls. 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 V.F) 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 noncorporate 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 noncorporate 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, whereas the effects of the personal income tax come from both mobility and innovation output responses.

Our article contributes to several strands of the growing literature on the effect 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 article.[2] Most closely related are Moretti and Wilson (2014, 2017), who study the effects of state taxes on the migration of star scientists across U.S. 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 (2019) 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 two-year period, while the corresponding estimate for the top 10% is insignificantly different from zero. Tax changes for the bottom 90% percent have large effects on 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 (2000); and 0.5–0.6 with appropriate controls

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 United States using administrative data.

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

in Saez, Slemrod, and Giertz (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 United States, 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 10-year period, a 3.74%–4.28% increase in population growth, and a 0.78%–1.45% increase in wage growth. Patel, Seegert, and Smith (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 article 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. A related strand of this literature studies the effects of policies like R&D tax credits on innovation (Bloom and Griffith 2001; Bloom, Griffith, and Van Reenen 2002; Goolsbee 1998, 2003). We always control for state-level R&D tax credits in our regressions.

The rest of the article is organized as follows. Section II provides a conceptual framework for linking micro individual-level and macro state-level elasticities. Section III describes the data and some key summary statistics. Section IV outlines the state-level analysis, results, and robustness checks, while Section V focuses on the inventor-level analysis. Section VI concludes. All appendix materials are in the Online Appendix.

II. 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.

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

Like other economic activities, innovation requires 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 noncorporate sector (by being self-employed), (iii) and which state to live in.[4]

The responses to taxes may differ for corporate and noncorporate 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, Devicienti, and Maida 2014; Aghion et al. 2018; Kline et al. 2019). Finally, corporate inventors can have different preferences and motivations than noncorporate ones. For example, they may 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 noncorporate), 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 noncorporate (personal) sector (p); they can also be

4. One margin of response that 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.

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 noncorporate 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 noncorporate inventors are $\varepsilon_{Y,p}^p$ and $\varepsilon_{Y,c}^p$. The production of the quality of innovation may also depend on net-of-tax returns:

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

with elasticities $\varepsilon_{Q,c}^c$, $\varepsilon_{Q,p}^c$, $\varepsilon_{Q,c}^p$, and $\varepsilon_{Q,p}^p$.

We assume that the production of innovation elasticities can differ across corporate and noncorporate inventors, but are homogeneous within these groups.[5] 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 may be highly elastic or, on the contrary, out of the control of inventors.

5. Although 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.

Inventors also choose which state to work in. Denote by $\eta_p^d := \frac{d\log(\int_{i\in I^d} di)}{d\log(1-\tau^p)}$ 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_p^o the elasticity with respect to the personal net-of-tax rate of out-of-state inventors (who can potentially move into the state).[6] Denote the corresponding migration elasticities with respect to the net-of-tax corporate rates by η_c^d and η_c^o.

At the state level, total innovation $Y := \int_{i\in I^d\cup I^o} y_i di$ 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:

(1)
$$\varepsilon_{Y,p} := \frac{d\log(Y)}{d\log(1-\tau^p)} = \gamma_Y^c \varepsilon_{Y,p}^c + (1-\gamma_Y^c)\varepsilon_{Y,p}^p + \gamma_Y^d \eta_p^d + (1-\gamma_Y^d)\eta_p^o,$$

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

(2)
$$\varepsilon_{Q,p} := \frac{d\log(Q)}{d\log(1-\tau^p)} = \gamma_Q^c \varepsilon_{Q,p}^c + (1-\gamma_Q^c)\varepsilon_{Q,p}^p + \gamma_Q^d \eta_p^d + (1-\gamma_Q^d)\eta_p^o,$$

where $\gamma_Q^c = \frac{\int_{i\in I^c} q_i di}{Q}$ with γ_Q^c the share of citations accruing to corporate inventors and γ_Q^d 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 zero-sum from the point of view of the United States as a whole.[7] 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, the more

6. We suppress the s and t subscripts for notational simplicity.

7. 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.

the macro elasticity is driven by the in-migration elasticity from other states, that is, 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, for example, 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, for example, 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 already, because the effects of the corporate tax on individual inventors are 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 V.F we show that the aggregation from the micro to the macro level works well quantitatively.

II.A. Dynamic Effects

The response to incentives for innovation can be dynamic. We explicitly consider this possibility using event studies (Section IV.C) and distributed lag models (Section IV.D).

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, for example, providing existing highly skilled R&D employees with more funding for experimentation. But, developing other innovations may require a much lengthier process of trial and error or adjusting scarce inputs sluggishly, for example, having to find highly specialized researchers to hire. In our benchmark analysis, we 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 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, that is, "pretrends"—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.

III. 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 Online Appendix A.1.

III.A. 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) (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 onward, 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.[8] Throughout our analysis, we assign a patent to a given year based on its application year

8. 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.

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 article 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 A.2, 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. We also test the sensitivity of our results to various alternative disambiguation routines. Our baseline disambiguation is the one that best balanced the false positive and false negative rates according to our tests.

Online Appendix Table C.1 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 U.S. inventors who were jointly granted 5.3 million patents. There are 1.74 million U.S.-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 (Trajtenberg 1990; Hall, Jaffe, and Trajtenberg 2001). 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, Jaffe, and Trajtenberg (2001).[9]

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

9. For more details, see Online Appendix A.5.

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 United States 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 effect. We also study inventors (and their location), as well as a range of other economic outcomes described next.

1. Descriptive Statistics at the Inventor and State Level. Table I 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 Online Appendix Table C.2; more detailed moments of the distributions of inventor career lengths, patents, citations, and mobility of inventors are in Online Appendix Table C.3. Unless otherwise stated, "citations" refer to our adjusted citation counts.

An inventor is considered "active" in any year between their first and last patent granted. Seventy percent 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 career length is highly skewed, with a 95th percentile of 15 years and a 99th 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

TABLE I
SUMMARY STATISTICS

	Mean (1)	Std. dev. (2)	1940–59 (3)	1960–79 (4)	1980–99 (5)
Inventor-level data: outcomes					
No. 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
No. 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 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					
No. patents (000s)	1.02	1.62	0.75	0.97	1.35
No. inventors (000s)	1.07	1.79	0.65	0.98	1.59
No. 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					
90th percentile income MTR	0.34	0.10	0.23	0.38	0.40
90th 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 90th 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	2,880	–	960	960	960
Sample composition					
% corporate patent	0.861	–	0.752	0.860	0.903
% home-state patent	0.860	–	0.861	0.873	0.853
% corporate citations	0.914	–	0.729	0.853	0.940
% home-state citations	0.845	–	0.868	0.875	0.838
% ever corporate inventor	0.835	–	0.704	0.842	0.887
% home-state inventor	0.854	–	0.863	0.849	0.852

Notes. This table reports summary statistics for our estimation sample. This includes all mainland U.S. states, excluding Louisiana, from 1940 to 2000. Columns (1) and (2) report the mean and standard deviation, respectively, for the full sample period, and 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, and "MTR" refers to tax rates inclusive of federal and state tax liabilities. "Home-state patents" are patents 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 Online Appendix Table C.2. 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 Online Appendix C.

and the most diversified top 1% of inventors have patents in 10 classes.[10] Although 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. Online Appendix Figure C.1 depicts patents per 10,000 residents at the state level for each decade; Online Appendix Figure C.2 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. Online Appendix Figure C.3 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.

III.B. 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. This method for estimating the quality of an innovation relies on a number of assumptions, including that the private value of a patent is always positive and that this value can be fully captured by stock market movements in a narrow event window around the patents grant—as opposed to its application—date. These data are available from 1926 to 2010 (with updates to 2019), and can be merged directly into our data set of patents by their patent number identifier. By construction, however, these data only capture the value of patents produced

10. The United States Patent Classification (USPC) system classifies patents based on the art's "proximate function." Patent classes may be retroactively updated as new technologies arise. We use the 2006 classification.

by publicly traded companies. Because the share of patenting in corporations has changed dramatically through time, as we just showed, we use this as a supplementary measure of innovation in this article.

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).[11] 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 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.

III.C. Historical Personal Income Tax Data

We compute state-level personal income taxes from the detailed tax calculator provided by Bakija (2006), which incorporates most tax-relevant considerations, such as federal tax deductibility, itemized deductions, and major tax credits.[12]

The evolution of personal income tax rates is described in Online Appendix C.2. First, Online Appendix Figure C.4 reports the first year in which each state introduced a personal income tax, and Online Appendix Figure C.5 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.

11. We thank Price Fishback and Sam Allen for graciously sharing these data with us.

12. The data for Louisiana are unreliable between 1975 and 1982. We therefore drop Louisiana from our main analysis sample.

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.

1. 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 given year. Data on median income come from the Census Bureau's Historical Income Tables. Data on the 90th percentile of incomes come from the World Inequality Database (Piketty and Saez 2003). From the Bakija (2006) 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 IV and explain how we assign tax rates to each individual inventor in Section V.

2. Key Tax Variation. Our empirical analysis makes use of the multitude of personal and corporate income tax changes that have happened since 1940. Online Appendix Figures C.6 and C.7 show the evolution of the marginal tax rates at the median and the 90th percentile income levels decade by decade.[13] Tax rates have followed very different trajectories across states–and have often also evolved differently from the federal tax rate.

Panel A of Online Appendix Figure C.9 depicts the percent of states with a change in their statutory state-level taxes for each year, as well as the mean size of the change, and the magnitude of the top 10 largest changes per year. The share of states changing their tax rate in any given year oscillates between 12% and 20% in the pre-1970s period and between 15% and 25% or even up to 40%

13. Online Appendix Figure C.8 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.

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. Online Appendix Table C.4 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 90th 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.

III.D. 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 incentives 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 also consider heterogeneous effects on corporate and noncorporate inventors, as they are likely to bear different loads from corporate taxes.

1. 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, including detailed state tax handbooks and legal statutes. 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 A.6. The raw corporate tax law data are available from the authors on request.

We first gather detailed apportionment rules for multistate 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. Online Appendix Figure C.14 shows the evolution of these apportionment rules over time. We 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 1958–1978, which we supplement with data from 1980 through 2010 from Suárez Serrato and Zidar (2018).

2. Construction of the Tax Rate and Base Measures. Our benchmark measure of corporate taxation will be the top corporate MTR, constructed using the top federal corporate tax rate and state and federal tax deductibility rules. Unlike personal income tax schedules, the state-level 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 Online Appendix A.6.2. 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.

3. Apportionment Rules and Multistate Inventors. Apportionment rules may also affect the interpretation of our estimated effects. 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 multistate 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 IV strategy below.

4. Other Taxes. Our identification strategies should filter out alternative taxes that may otherwise affect 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.

5. 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. Over time, the share of states with direct corporate income taxes rather than indirect taxes has increased (see Online Appendix Figure C.11).

Online Appendix Figure C.12 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). Online Appendix Figure C.13 shows the evolution of the top corporate MTRs 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 nonzero 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. 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%.[14] Finally, Online Appendix Figure C.14 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.

14. The patterns summarized here, as well as the evolution of top corporate tax rates in a few select states, are also presented in Online Appendix Figure C.11.

6. Key Corporate Tax Variation. Panel B of Online Appendix Figure C.9 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 90th percentile largest change for each year. On average, one out of every six or seven 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 1980s. The mean tax change fluctuates around 1.5–2 percentage points, and the largest top 10% tax changes reach up to 6 percentage points.

IV. The Macro Effects of Taxation

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

IV.A. Benchmark Estimation

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, that is, inventors transferring patents to their employer through assignment rights. We consider additional state-level outcomes shortly. Our baseline specification is:

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

where Y_{st} is one of the innovation outcomes in state s and year t. $MTR90_{st-3}$ is the state's three-year lagged personal income MTR at the 90th percentile of income and Corp. MTR_{st-3} is the three-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, lagged real personal income per capita, and R&D tax credits (lagged by three 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 three-year lags because of the dynamics visible in the event studies, but we test the sensitivity to these specifications later. 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 relax this assumption using an IV strategy.[15] 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.

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 nontax 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 upward. To do so, we estimate our core specification from equation (3) in long differences of 10, 15, or 20 years, that is, for $k \in \{10, 15, 20\}$:[16]

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

2. Results. Table II, Panel A shows the estimates from the state-level regressions in equation (3).[17] Each column represents one of the innovation outcomes Y_{st} described above. A 1% decrease in MTR90 (equivalently, a 1% increase in the net-of-tax

15. 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 semielasticities.

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

17. Online Appendix Table C.5 reports the coefficients on all control variables.

TABLE II
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	2,867	2,867	2,867	2,867
Mean of dep. var.	7.07	9.65	7.08	0.72
Std. dev. 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 $\times \ln(1 -$ corp. MTR$)$	0.220*	0.198	0.279**	0.026
	(0.124)	(0.140)	(0.119)	(0.018)
Observations	2,256	2,256	2,256	2,256
Mean of dep. var.	7.17	9.86	7.24	0.76
Std. dev. 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	2,867	2,867	2,867	2,867
Mean of dep. var.	7.07	9.65	7.08	0.72
Std. dev. of dep. var.	1.33	1.56	1.34	0.14

Notes. This table reports estimates from a regression following equation (3). Robust standard errors two-way clustered at state × five-year and year level are 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 three 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 equations (6) and (8) respectively. Panel C reports OLS estimates that also 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, are included for the period 1940–2000. * $p < .1$, ** $p < .05$, *** $p < .01$.

retention rate at the 90th percentile) is associated with an approximately 1.8% increase in patents and inventors and a similar 1.5% increase in citations. The corporate tax is also significantly correlated with innovation outcomes. A 1% 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—that is, 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 1% increase in the top corporate tax rate is associated with close to 0.6 percentage point fewer patents assigned to companies. Online Appendix Table C.6 shows that corporate patents are indeed more sensitive to the corporate tax than noncorporate 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, Table II, Panel B 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 including 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 III reports estimates from the long-difference specification in equation (4). As foreshadowed, 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 semielasticity of 0.4, 0.3, or 0.16 in these three long-difference specifications.

To visualize these results, Figure I 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

TABLE III
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)
$\Delta\ln(1 - \text{corp. MTR})$	1.980***	1.877***	1.752***	0.442***
	(0.243)	(0.277)	(0.230)	(0.082)
Observations	1,927	1,927	1,927	1,927
Mean of dep. var.	0.29	0.81	0.44	0.09
Std. dev. 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)
$\Delta\ln(1 - \text{corp. MTR})$	1.511***	1.216***	1.325***	0.313***
	(0.250)	(0.298)	(0.247)	(0.062)
Observations	2,162	2,162	2,162	2,162
Mean of dep. var.	0.26	0.66	0.37	0.07
Std. dev. 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)
$\Delta\ln(1 - \text{corp. MTR})$	1.317***	0.972**	1.242***	0.163*
	(0.306)	(0.391)	(0.325)	(0.090)
Observations	2,397	2,397	2,397	2,397
Mean of dep. var.	0.20	0.46	0.27	0.05
Std. dev. of dep. var.	0.37	0.54	0.36	0.09

Notes. This 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, and Panel C considers 10-year long differences. Standard errors clustered at the year level are reported in parentheses. All regressions include controls for long differences in personal income/capita, R&D tax credits, population density, and the corporate tax base index, as well as year fixed effects. Regressions are weighted by 1940 state population. * $p < .1$, ** $p < .05$, *** $p < .01$.

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 V.F, we discuss how these large macro elasticities are consistent with the aggregation of the micro-level elasticities estimated in Section V. The magnitudes are in line with the typically large macro-level elasticities estimated for other variables such as GDP in the United States at the federal level.

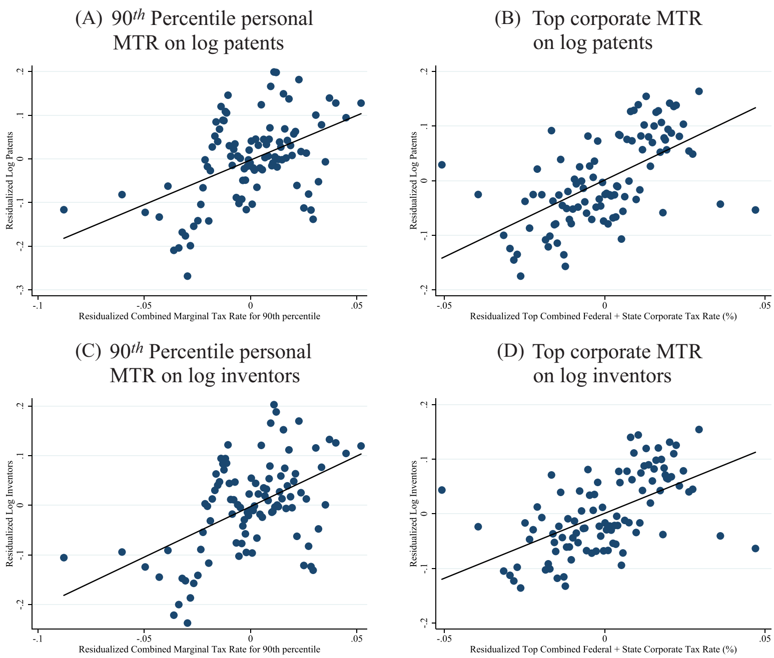

FIGURE I

Binned Scatters

This figure plots binned scatter plots for the effect of taxes at the state level. The top row shows the effect on log patents, and 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 shows the 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 also residualize against the lagged corporate tax rate, while Panels B and D residualize against 90th percentile personal income MTR. All mainland U.S. states except Louisiana are included over the period 1940–2000.

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% and 3%, using a narrative approach to isolate exogenous federal-level tax changes (in Section V.F we discuss why federal-level elasticities could reasonably be expected to be smaller than state-level ones). Mertens and Ravn (2013) find that a 1 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 three quarters. A 1 percentage point cut in the average corporate income tax rate increases real GDP per capita by 0.4% and up to 0.6% after four quarters. Mertens and Ravn (2014) find that a tax cut that lowers tax revenues by 1 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 that can be viewed as the final "output" of a function of various inputs, for example, 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.

3. Robustness Checks and Extensions. These results are robust to a variety of alternative specifications, controls, and sample restrictions, provided in Online Appendix C.3 and summarized here.

First, Online Appendix Table C.6 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 noncorporate patents, but both respond similarly to personal taxes, which is consistent with the conceptual discussion in Section II. 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, that is, average employment of manufacturing establishments, manufacturing value added, total manufacturing payroll, average weekly earnings, income per capita, and the share employed in manufacturing are 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.

Online Appendix Table C.7 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. Online Appendix Table C.8 simultaneously includes the personal income MTRs for both the median and the 90th percentile income levels and shows that the latter dominates. Overall, the association between innovation and our benchmark MTR 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 (Online Appendix Table C.9), itemizing deductions rather than taking the standard deduction if it is optimal to do so (Online Appendix Table C.10), using effective federal corporate tax rates from Auerbach and Poterba (1987) to compute our total corporate tax rate (Online Appendix Table C.11), and changing the tax rate lag to one or two years (Online Appendix Table C.12). 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 (Online Appendix Table C.13).

The relationship between taxes and innovation also does not meaningfully change across a number of sample restrictions, for example, dropping observations from the two largest and most innovation-intensive states (California and New York) in Online Appendix Table C.14 or from a period with unusually low innovation (the 1970s) in Online Appendix Table C.15.

The results are also robust to including or removing additional control variables. Online Appendix Table C.16 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). Online Appendix Table C.17 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 Online Appendix Table C.18 shows.

IV.B. IV 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 IV 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 effect 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}.[18] Heuristically, ignoring complications of the tax code, the total tax rate on individuals with income at the *jth* percentile who live in state s at time t is denoted by τ^{pj}_{st} and is equal to:

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

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 deducting 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

18. 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.

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_{st}^{pj}.[19]

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

$$\tau_{st}^{c} = \tau_{ft}^{c}(1 - \tilde{\tau}_{st}^{c}) + \tilde{\tau}_{st}^{c}(1 - D_{st}^{c} \cdot \tau_{ft}^{c}), \tag{7}$$

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

$$\hat{\tau}_{st}^{c} = \tau_{ft}^{c}(1 - \tilde{\tau}_{st-k}^{c}) + \tilde{\tau}_{st-k}^{c}(1 - D_{st-k}^{c} \cdot \tau_{ft}^{c}). \tag{8}$$

Figure II visualizes the source of variation in this instrument. The gray bars plot the change in the federal tax rate for the 90th 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 preexisting state tax laws. The squares connected with dashed lines show the 90th percentile of the change in state tax rates as a result of this federal tax law change, and the circles connected with solid lines plot 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 preexisting tax rates $\tilde{\tau}_{st-k}^{p}$, $\tilde{\tau}_{st-k}^{c}$ and deductibility rules D_{st-k}^{p}, D_{st-k}^{c}. 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 Online Appendix Table C.4 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 (Online Appendix Table C.19).

The IV results are in Table II, Panel C. They are highly significant and slightly larger than the OLS ones. One potential

19. Note that even if states anticipate federal 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.

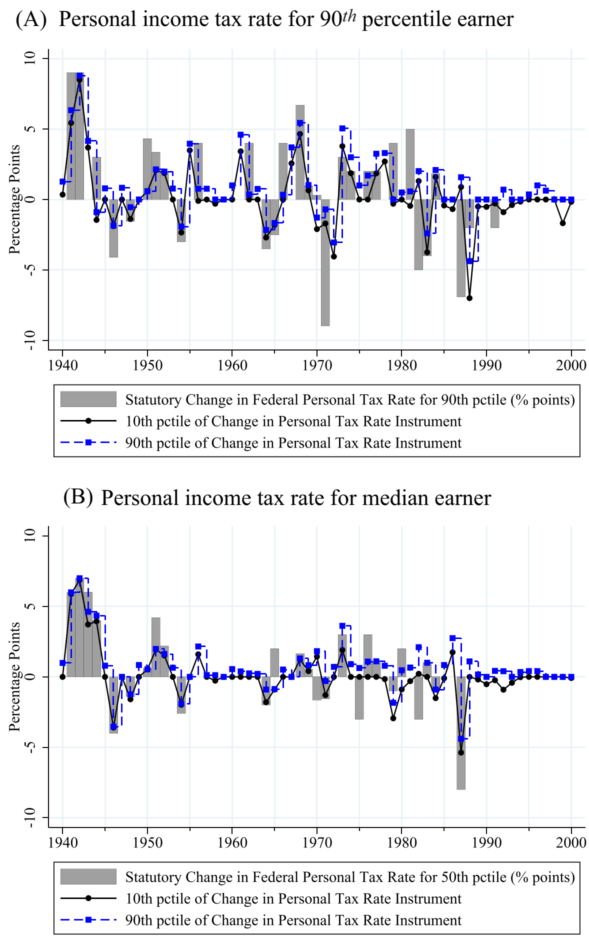

FIGURE II

Visualizing IV Variation

This 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 squares connected by dashed lines plot the 90th percentile of induced tax changes, and the circles connected by solid lines plot the 10th percentile of induced tax changes. The income distribution is lagged by five years to produce this plot. That is, the dashed and solid 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 equation (6).

explanation for this magnitude may be that states are adjusting their tax rates in a countercyclical fashion, which would bias the OLS estimates downward if innovation is procyclical.

IV.C. 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 I), 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 nine years, a span length chosen to be as large as possible, while also avoiding too many overlapping reforms.[20] We drop from the sample tax reforms that 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 four 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 prereform 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

20. Increasing the event window to be longer than four years necessitates dropping many large reforms due to the increased presence of overlapping reforms. Online Appendix Figure C.15 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.

data set and estimate the following regression:

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

where r indexes a reform, s is a state, t is the number of years since the reform, $\boldsymbol{TREAT}_s$ 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 $\theta_r \times \boldsymbol{TREAT}_s$ are reform and reform-by-treated state fixed effects.

Figure III 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 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 II and with our use of three-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% 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 of 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.

1. Case Studies. We investigate three special episodes of comprehensive tax reform in New York, Delaware, and Michigan. We again use synthetic control techniques to provide sharp visual evidence of the effects of taxes on innovation. These results are in Online Appendix C.5 and Figures C.16–C.18. 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.

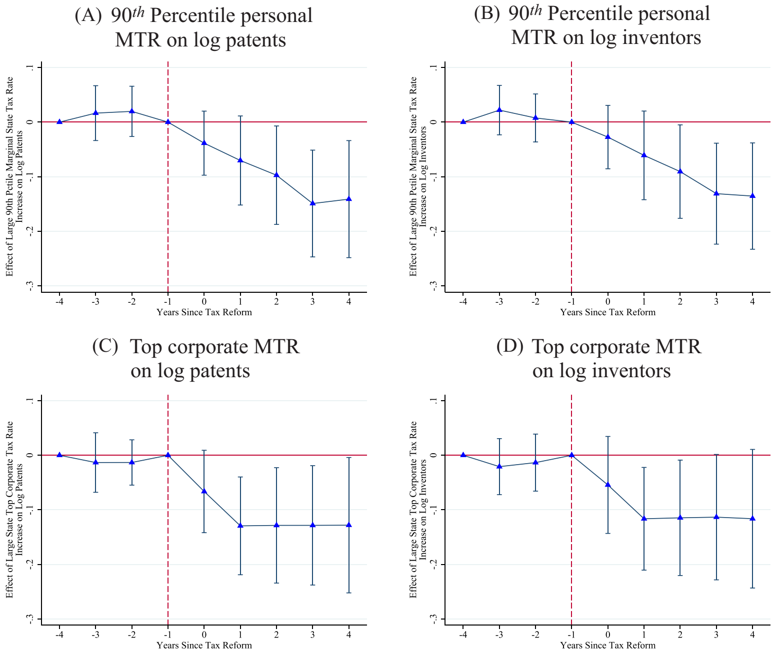

FIGURE III

State-Level Event Studies around Large Tax Reforms

This 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 four years before or after the focal reform. Panels A and B consider state tax reforms affecting the personal tax rate for the 90th 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, Diamond, and Hainmueller (2010) by matching on prereform outcomes (patents or inventors), population density, and personal income/capita averaged over the four years before 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 IV.C for details. All regressions include reform × 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.

IV.D. 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

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

where $T \in \{MTR90, \text{Corp. Tax}\}$ is either the top corporate tax rate or the marginal personal income tax rate at the 90th 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 nonfocal tax rate (e.g. if T studies corporate taxes, we 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 IV plots the cumulative effects $\mathcal{B}_l$ of a tax change in year t on innovation by year $t + l$, for $l \in \{-5, \ldots, 20\}$, where:

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

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

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 three-year lag of tax rates). After 20 years, a 1% increase in the net-of-personal tax rate is associated with an approximate 2% 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.

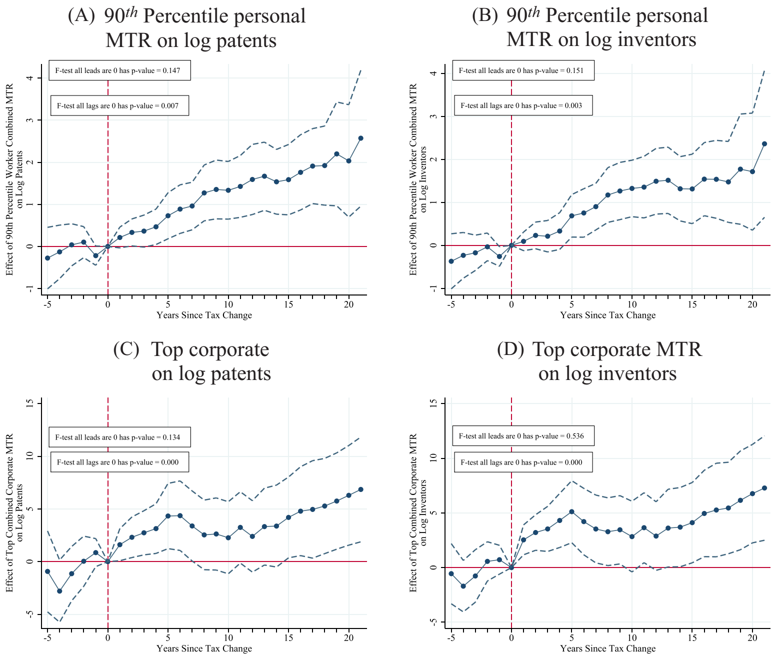

FIGURE IV

State-Level Distributed Lag Regressions

This 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 zero. Coefficients may thus be interpreted as cumulative elasticities. See Section IV.D for details. All regressions include one-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 also 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 state and federal tax liabilities. Dashed lines indicate 90% confidence intervals calculated using standard errors clustered at the state level.

Overall, as emphasized in Section III.D, measurement issues are much more constraining and make the estimated effects of corporate taxes noisier and less stable than those of personal tax rates.

V. 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.

V.A. 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. Implementing 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.

1. 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 U.S. inventors and 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 with our benchmark measure of inventor productivity in year t, we use total patents produced until year t, but test sensitivity to this choice later.

2. Measuring an Inventor's Tax Rate. Using this productivity measure, we can rank inventors nationwide 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. Of the inventors who are classified as being high productivity in year t, 99.1% 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.

3. 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 $t + 2$:[21] (i) whether the inventor has any patent; (ii) whether the inventor has a successful patent with at least 10 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.

V.B. Identification

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

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

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

where Corp. Tax is the top corporate tax rate in the state and the term $\ln(1 - \text{PersonalMTR}_{it-3}) = [\chi_{it-1}\ln(1 - MTR90_{s(i)t-3}) + (1 - \chi_{it-1})\ln(1 - MTR50_{s(i)t-3})]$ 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 90th percentile and median individual in a state, and χ_{it} is an indicator variable equal to 1 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 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, stealing ideas, 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 × year fixed effects). Recall, however, from the conceptual discussion in Section II and the measurement issues outlined in Section III.D 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 equation (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.

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

Here, $\mathbb{X}_{it-1}$ is the same as before, except we remove 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 apply the same IV strategy as for the macro state-level regressions 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 inventors 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 tax changes be uncorrelated with unobserved determinants of individual innovation.[22] 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.

V.C. *Results*

Table IV shows the benchmark results. The upper panel reports the estimates from the specification with state $\times$ year fixed effects in equation (13); the lower panel shows the specification with only state and year fixed effects from equation (12). The out-

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

TABLE IV
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)
Panel A: State × year fixed effects					
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
Panel B: State and year fixed effects					
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	6,460,412	6,460,412	4,566,398	4,415,498	1,485,493
Mean of dep. var.	0.707	0.422	0.458	2.779	0.500
Std. dev. 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. This table reports coefficients estimated from OLS regressions at the individual inventor level. Standard errors two-way clustered at the state and year level are 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, are included for the period 1940–2000. Personal MTR is defined as the marginal tax rate faced by the 90th percentile earner in state s in year t for high-productivity inventors, and the marginal tax rate faced by the median earner for low-productivity inventors. High-productivity inventors are defined to be those who are in the top 10% of the national distribution of cumulative patents among active inventors. See Section V.A for details. Tax rates are lagged by three 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: column (1) an indicator for whether the inventor has a patent, column (2) an indicator for whether the inventor has at least 10 citations, column (3) the natural log of patents, column (4) the natural log of citations received, and column (5) an indicator for whether an individual has patents with above-median Kogan et al. (2017) patent value. * $p < .1$, ** $p < .05$, *** $p < .01$.

come variables listed in columns (1)–(5) are as defined in (i)–(v) above.[23]

23. For the indicator outcomes in columns (1), (2), and (5), the coefficients can be interpreted as semielasticities 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.

The estimated effects of personal income taxes are very similar in the two panels, suggesting that the state × year fixed effects are not critical to the estimation. Focusing on panel A, a 1% higher tax rate at the individual level decreases the likelihood of having a patent in the next three 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 1% increase in the personal tax rate is associated with a 0.8% 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 (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 1% 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 panel B, the effects of the corporate net-of-tax rate are consistently positive but insignificant. Below we show that this overall null effect masks heterogeneous effects on corporate and noncorporate inventors as well as a sizable effect on inventors' mobility across states.

Online Appendix Table C.21 presents the IV results at the individual-inventor level.[24] They are very similar to and slightly larger than the OLS estimates.

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, for example, allowing inventors in the top

24. The associated first-stage regressions are reported in Online Appendix Table C.22.

5% or the top 25% to be assigned the 90th percentile personal income tax rate (see Online Appendix Tables C.23 and C.24). 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 Online Appendix Table C.25). The results also look very similar if we define inventor productivity according to their cumulative citation counts (Online Appendix Table C.26).

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%) as in Akcigit, Baslandze, and Stantcheva (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 Online Appendix Table C.27. 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 (Online Appendix Table C.28) or the 1970s (Online Appendix Table C.29); to removing the controls for personal income per capita, agglomeration forces, and population density (Online Appendix Table C.30); and using the tax rate for married couples instead of singles (Online Appendix Table C.31). The results are also robust to excluding inventor fixed effects, but the results are noisier (Online Appendix Table C.32).

The IV estimates are robust to alternative constructions of the instruments. To address the concern that inventors endogenously change their location choice to respond to taxes, in Online Appendix Tables C.33 and Table C.34 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.

2. Changing Effects of Taxes over Time. The long time span of our data permits analysis of the potentially changing repercussions of taxes over time. Estimating equation (12) allowing for a differential effect of taxes for the periods before and after 1970 (Online Appendix Table C.35) 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 multistate corporate taxation towards a sales-based apportionment could also have contributed.

3. Agglomeration Effects. As discussed already, 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 to control for general (non–field specific) amenities at the state level. The results in Online Appendix Table C.36 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.

V.D. 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 V.A (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

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

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 that are among the 15 most-inventive states, as measured by total patents over the period 1940–2000, and have spells with a progressive state tax system (that is, 90th percentile earners pay a higher MTR 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 before, total patents granted to inventors other than i in state s in year t in inventor 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 effects in different states). "Assignee has Patent in Destination" is an indicator equal to 1 if the employer of the inventor already has had one patent in the state under consideration. In regressions that 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 in a given year, and because the computations are very demanding, we prioritize arbitrary spatial correlation in error terms by clustering at the year level.

Table V, column (1) shows the specification with state plus year fixed effects; all other columns include state × year fixed effects, making use of the same logic for identification as explained already.[25] The coefficients represent changes in the log-odds ratio of locating in state s associated with a one-unit increase in the independent variable; because 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, Landais, and Saez (2013) and Akcigit, Baslandze, and Stantcheva (2016), summarized in Online Appendix B.

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 × 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 effect 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 inven-

25. In columns with state × year fixed effects, only state-years with progressive personal taxes are included, as the others' taxes are absorbed in the state × year fixed effects.

TABLE V
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	4,197,104	2,002,776	2,002,776	2,002,776

Notes. This table reports coefficients estimated from the multinomial logistic regression specified in Section V.D. $ATR^{pj[i]}$ represents the average personal tax rate faced by an individual i who is at the jth income percentile locating in a given state and year. We assign tax rates to inventors following the procedure laid out in Section V.D. White heteroskedasticity-robust standard errors clustered at the year level are 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)) also controls for one-year lags of state personal income per capita, population density, R&D tax credits, agglomeration × high productivity and our index of corporate tax base breadth. For the sake of computational feasibility, we restrict attention to the 8 states that are among the 15 most-inventive states by total patent counts and ever have a progressive tax spell (i.e., charge a different marginal tax rate to 90th 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, normalized to have mean zero and unit standard deviation. 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, Landais, and Saez (2013) and described in Online Appendix B. * $p < .1$, ** $p < .05$, *** $p < .01$.

tors. 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 inventor-level innovation, agglomeration influences not only the value an inventor derives from being in a state, 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 because of career concerns or lower frictions of moving to a state where the employer already has a physical presence.

V.E. Corporate Inventors

Although Table IV 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 noncorporate inventors. We thus reestimate equation (12) interacting corporate and personal income tax rates with indicators for whether the inventor is a corporate or noncorporate inventor. As before, an inventor is defined as a corporate inventor in year t if they have at least one patent assigned to a company over the next three years. Specifically, we estimate

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

where C_{it} is an indicator equal to 1 if the inventor is a corporate inventor in year t, υ_{it} is an error term, and every other variable is as described in equation (12). Included in the $\mathbb{X}_{it}$ 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

TABLE VI

CORPORATE VERSUS NONCORPORATE INVENTOR ELASTICITIES

	Corporate inventors		Noncorporate inventors	
Tax type	Personal (1)	Corporate (2)	Personal (3)	Corporate (4)
No. 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)
No. 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 reports 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, and columns (3) and (4) report them for noncorporate 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 IV. 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 are reported in parentheses. The first two rows report elasticities defined as the estimated semielasticity 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 "No. citations, conditional > 0" (the second and third rows). Mobility elasticities are calculated by estimating multinomial logistic regressions following equation (14) and following the procedure of Kleven, Landais, and Saez (2013) as described in Online Appendix B. These multinomial regressions are estimated analogously to column (1) of Table V and include state plus year fixed effects and all the same control variables. * $p < .1$, ** $p < .05$, *** $p < .01$.

innovation outcome to personal and corporate taxes, for corporate and noncorporate inventors.

Table VI reports the estimated elasticities for corporate and noncorporate 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 noncorporate inventors shows no statistically significant response to the corporate tax. The personal net-of-tax rate, however, strongly influences the patenting activity of noncorporate inventors and to a lesser degree that of corporate inventors.

The quality of innovation also 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 noncorporate inventors. Overall, the average quality of corporate inventors is again insensitive to taxes, while that of noncorporate inventors is somewhat negatively affected by personal and corporate taxes, that is, 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 noncorporate 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 noncorporate inventors respond strongly to both corporate and personal tax rates, with an elasticity of 0.72 to the personal tax and 0.60 to the corporate tax.

On balance, the small and insignificant effect of corporate taxes on noncorporate inventors and their strong significant effects on corporate inventors' innovation contributes to the positive insignificant effect for the full sample in Table IV. The fact that lower corporate taxes tend to stimulate corporate innovation more than noncorporate 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 II).

V.F. 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 II holds formally true, in practice there can 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 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, that is, 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 III, 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 × year fixed effects, or the agglomeration measure, control for such state-level time-varying price effects.[26]

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

26. 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, that is, $y_{it} = y_i(1 - \tau^p, 1 - \tau^c, \mathbb{P}(\tau^p, \tau^c))$. 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 brackets as the state × year fixed effects and the time-varying inventor-level controls will filter out many or most of the general-equilibrium effects going through $\mathbb{P}$. Thus, while the decomposition in Section II is accurate, the fact that identification does not come from the same variation at the micro and macro levels introduces a wedge.

These considerations aside, we can use the formulas in Section II 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 noncorporate inventors ($\varepsilon^{p}_{Y,p}$) from Table VI, the location choice elasticities η^{d}_{p} and η^{o}_{p} from Table V 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 I, 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 II and slightly above the elasticities estimated using our long-differences specification, which range from 0.78 to 1.45 (Table III). Repeating the 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 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 III, 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 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 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 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 U.S. innovation on federal tax rates. We use the Auerbach and Poterba (1987) effective corporate tax rates for this exercise to capture federal corporate tax base changes. The results are reported in Online Appendix Table C.20, which shows that the federal 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 because 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.

VI. Conclusion

In this article, 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 data sets. 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 just to tax rates, which are merely a component of that economic calculation.

In future work, it would be fruitful to compare the U.S. experience to other countries, historically and contemporaneously. That would require a major data collection effort, as we have completed for the United States, but our analysis highlights the benefits of such investments. Although 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 United States, 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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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

Data and code replicating the tables and figures in this article can be found in Akcigit et al. (2021) in the Harvard Dataverse, https://doi.org/10.7910/DVN/SR410I.

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