TAXATION AND INNOVATION IN THE 20TH CENTURY

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ABSTRACT

This paper studies the effect of corporate and personal taxes on innovation in the United States over the twentieth century. We use three new datasets: a panel of the universe of inventors who patent since 1920; a dataset of the employment, location and patents of firms active in R&D since 1921; and a historical state-level corporate tax database since 1900, which we link to an existing database on state-level personal income taxes. Our analysis focuses on the impact of taxes on individual inventors and firms (the micro level) and on states over time (the macro level). We propose several identification strategies, all of which yield consistent results: i) OLS with fixed effects, including inventor and state-times-year fixed effects, which make use of differences between tax brackets within a state-year cell and which absorb heterogeneity and contemporaneous changes in economic conditions; ii) an instrumental variable approach, which predicts changes in an individual or firm's total tax rate with changes in the federal tax rate only; iii) a border county strategy, which exploits tax variation across neighboring counties in different states. We find that taxes matter for innovation: higher personal and corporate income taxes negatively affect the quantity, quality, and location of inventive activity at the macro and micro levels. At the macro level, cross-state spillovers or business-stealing from one state to another are important, but do not account for all of the effect. Agglomeration effects from local innovation clusters tend to weaken responsiveness to taxation. Corporate inventors respond more strongly to taxes than their non-corporate counterparts.

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

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

1   Introduction

Major reform to the U.S. tax code under the 2017 Tax Cuts and Jobs Act has renewed interest in the long-standing question – 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? Do they affect where inventors decide to locate and what firms they work for? Do they affect where companies allocate R&D resources and how many researchers they employ?

Answers to these questions, while crucial to a clearer understanding of one of the most vexing current public policy issues, have remained elusive due to a paucity of empirical evidence. In fact, in the absence of systematic data, ambivalence towards tax policy may stem from a reliance on isolated cases or anecdotes to confirm or reject particular viewpoints. The gap in our knowledge is especially large when trying to understand the impact of tax policy on technological development over the long-run. Although the United States experienced major changes in its tax code throughout the twentieth century, we currently do not know how these tax changes influenced innovation at either the individual, corporate or state levels.

In this paper, we both bridge the data gap and provide new evidence on the effects of taxation on innovation. Our goal is to systematically analyze the effects of both personal and corporate income taxation on inventors as well as on firms that do R&D over the 20th century. To our knowledge, this has never been done before because of the lack of data. Our analysis leverages three new datasets. First, we construct a panel dataset on inventors based on digitized historical patent data since 1920. These panel data allows 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 build a dataset on firms' R&D activities over the twentieth century, specifically the number of laboratories operated and research employment. These data were obtained from National Research Council (NRC) Surveys of *Industrial Research Laboratories of the United States* (IRLUS) for the period 1921 to 1970.

Third, we combine the new inventor-level panel data and firm-level R&D data with a new dataset on historical state-level corporate income taxes and a database on personal income tax

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rates.[1] The corporate tax data were compiled from a range of handbooks and reference-works. The result of this extensive data collection effort is a comprehensive historical dataset, covering individual inventors, R&D labs and research workers of firms, and taxation at the corporate and personal levels for much of the twentieth century in the United States. Due to the richness of our data, we can analyze the impact of taxes on innovation for both individuals and firms.

We provide a conceptual framework to help motivate our analysis and interpret the various effects of taxes on innovation that we identify. This framework has the following intuition. Consider an innovation production function in which the quantity and quality of innovation result from costly investments in research expenses and effort. Inventors can work for firms or be self-employed. Personal and corporate income taxes affect the net return to innovation. Since innovation inputs are costly, they exhibit elasticities to net returns, the magnitudes of which will depend on the market environment. If inventors work for firms, for example, their compensation derives from surplus sharing with the firm.[2] As a result, both firms and their inventors could be responsive to both personal and corporate income taxes. These effects, in turn, may reflect a mix of extensive margin responses (inventors or firms moving across states, individuals making occupational choices, and entering or exiting the labor market) and intensive margin responses (inventors choosing how hard to work on their research, companies choosing how many employees to hire).

Our empirical analysis starts at the macro, state-level, moves to some salient case studies, and then to the micro-level of individual firms and inventors.[3] We propose several different strategies to identify the impact of taxes on innovation. First, we control for a detailed set of fixed effects, including state, year and, at the individual-level, inventor fixed effects, plus individual or state-level time varying controls. These help to absorb unobserved heterogeneity. In addition, 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 × year fixed effects. These controls filter out other policy variations or the effect of contemporaneous economic circumstances in the state. Second, at the macro and micro levels, we use an instrumental variable approach which predicts the total tax burden facing a firm or inventor – which is a composite of state and federal taxes – with changes in the federal tax rate only, holding state taxes fixed at some past level. This provides variation driven only by federal level changes so is plausibly exogenous to any individual state. Third, we use a spatial border county strategy, which exploits tax variation across neighboring counties that lie in different states. We also implement this border county strategy in combination with our IV approach. Finally, we provide evidence of the impact of taxes on innovation using specific episodes of sharp tax changes.

We begin by describing patterns in innovation and taxation over the 20th century. We focus

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[1] Personal income taxes provided by Jon Bakija, who constructs a large scale tax calculator program to model federal and state personal income taxes from 1900 through 2016 (Bakija, 2017).

[2] For empirical evidence on the surplus sharing between firms, entrepreneurs, workers and inventors see Aghion et al. (2018) and Kline et al. (2017).

[3] It is worth noting that we are interested in the effects of general taxation, i.e., corporate and personal income taxation, not specifically in innovation focused policies such as R&D tax credits, although we do control for those.

on key facts in relation to inventors, making use of the new panel data to show where inventors located over time, where firms' R&D labs were placed, and trends exhibited by the time series of patents, citations, and research lab employment. We then document central patterns in taxation on personal and corporate income over the 20th century in the U.S, focusing specifically on our newly constructed corporate tax database.

Next we focus on macro state-level results. We use OLS to study the baseline relationship between taxes and innovation, exploiting within-state tax changes over time, our instrumental variable approach and the border county design. On the personal income tax side, we consider average and marginal tax rates, both for the median income level and for top earners. Our corporate tax measure is the top corporate tax rate. We find that personal and corporate income taxes have significant effects at the state level on patents, citations (which are a well-established marker of the quality of patents), inventors and "superstar" inventors in the state, and the share of patents produced by firms as opposed to individuals. The implied elasticities of patents, inventors, and citations at the macro level are between 2 and 3.4 for personal income taxes and between 2.5 and 3.5 for the corporate tax. We show that these effects cannot be fully accounted for by inventors moving across state lines and therefore do not merely reflect "zero-sum" business-stealing of one state from other states. Our instrumental variable estimation results and the border county strategy confirm the OLS fixed effects findings.

We then turn to the micro-level, i.e., individual firms and inventors. In addition to many detailed inventor-level (fixed and time varying) controls, we are able to include state $\times$ year fixed effects to control for other possible policies that may have occurred simultaneously with tax changes. Hence, we exploit within state-year variation. We make use of the fact that inventors of different productivities have different incomes and will therefore be subject to different tax brackets. We also implement our aforementioned instrumental variable approach at the individual-level. Again, we find that taxes have significant negative effects on the quantity and quality (as measured by citations) of patents produced by inventors, including on the likelihood of producing a highly successful patent (which gathers many citations). At the individual inventor level, the elasticity of patents to the personal income tax is 0.6-0.7, and the elasticity of citations is 0.8-0.9.

Furthermore, we show that individual inventors are negatively affected by the corporate tax rate, but much less so than by personal income taxes. Corporate inventors are much more elastic to personal and corporate income taxes than non-corporate inventors (individual "garage" inventors operating outside the boundaries of firms), and are especially strongly elastic to the corporate tax rate. We also show that an inventor is less sensitive to taxes when there is more agglomeration – i.e., more inventors in the same technological field in the state. At the individual firm-level, we find that corporate taxes – and to a lesser extent, personal income taxes – have significant negative effects on the level of patents, citations, and research workers employed in corporate R&D laboratories.

Finally, we estimate a location choice model, in which inventors can choose in which state to reside, trading off state characteristics against the effective tax rate in each state, conditional on state $\times$ year fixed effects. We find that inventors are significantly less likely to locate in states with

higher taxes. The elasticity to the net-of-tax rate of the number of inventors residing in a state is 0.11 for inventors who are from that state and 1.23 for inventors not from that state. Inventors who work for companies are particularly elastic to taxes. Agglomeration effects appear to matter for location as well: inventors are less sensitive to taxation in a potential destination state when there is already more innovation in that state in their particular field of inventive activity. This is also true if an inventor's employer already has a record of innovation activity in that state. We confirm that firms are responsive to corporate taxes when choosing where to locate by estimating a location choice model at the individual R&D lab level.

Our main findings can therefore be summarized as follows. Taxation – in the form of both personal income taxes and corporate income taxes – matters for innovation along the intensive and extensive margins, and both at the micro and macro levels. Taxes affect the amount of innovation, the quality of innovation, and the location of inventive activity. The effects are economically large especially at the macro state-level, where cross-state spillovers and extensive margin location and entry decisions compound the micro, individual-level elasticities. Not all the effects of taxes at the macro-level are accounted for by cross-state business stealing or spillovers. Corporate inventors are most sensitive to taxation; and positive agglomeration effects play an important role, perhaps in offering a type of compensating differential for taxation.

As a final note, while our analysis focuses on the relationship between taxation and innovation, our data and approach have much broader implications. We find that taxes have important effects on intensive and extensive margin decisions, on the mobility of people and where inventors and firms choose to locate. So far, any rigorous analysis of these kinds of effects has been impossible due to a lack of long-run data. Our new inventor panel data, which stretches back to the early twentieth century allows us to uniquely track individuals each year. To the extent that innovation is the outcome of investment and effort, just like a range of other important pursuits such as entrepreneurship, the magnitudes of the elasticities to taxation we find at the micro and macro levels on the extensive and intensive margins can help us bound the effects on other types of economic activities and agents.

1.1 Related Literature

To our knowledge no systematic study has yet been conducted on the effect of personal and corporate taxation on innovation by individuals or firms over a long time horizon. Butters and Lintner (1945) conducted an influential analysis of the impact of federal individual and corporate taxes on the growth prospects of small and large firms during the 1930s and early 1940s finding the effects were largely negative, especially the impact of corporate tax on the growth rate of larger firms. However, their evidence was based on only five firm-level case histories and they did not explicitly address the relationship between taxation and innovation.

Our work contributes to the abundant and growing literature on the empirical effects of taxes. It is related to work on the effects of personal taxes – on income or wealth– using data from recent

time periods. Often, the focus of this research is on the taxable income elasticity (Gruber and Saez, 2002; Saez, Slemrod, and Giertz, 2012), but many specific and varied margins have been shown to be affected by taxation. These include work contracts set by companies (Chetty, Friedman, Olsen, and Pistaferri, 2011), the self-employed's reported income (Kleven and Mazhar, 2013; Saez, 2010), rent-seeking (Piketty et al., 2014), or charitable contributions (Fack and Landais, 2010). At the more macro level, Zidar (2017) studies how tax changes for different income groups affect aggregate economic activity, finding that employment growth is mostly caused by tax cuts for lower-income groups, but that the impact of tax cuts for the top 10% on employment growth is much smaller. Kleven, Jakobsen, Jakobsen, and Zucman (2018) undertake a rare study of the effects of wealth taxes on wealth accumulation given that such data are difficult to find.

Most directly related is the body of work considering the effect of personal income taxes on entrepreneurship. Cullen and Gordon (2006, 2007) study the effect of taxes and their progressivity on entrepreneurial activity and risk-taking by entrepreneurs. Gordon and Lee (2005) consider the link between taxes and economic growth – our paper is novel in that it highlights innovation as one of the channels through which this link can occur.

On the corporate tax side, several empirical studies examine the effects (or absence thereof) of dividend tax cuts (Yagan, 2015; Chetty and Saez, 2005). A large focus has been on the effects of corporate and personal income taxes on the shifting behavior and evasion (Gordon and Slemrod, 2000; Slemrod, 2007) by firms and individuals. Slemrod and Shobe (1989) consider the elasticity of capital gains realizations. Poterba (1989) investigates the relations between capital gains taxation and the level of venture capital activity and entrepreneurship. Mahon and Zwick (2017) study the heterogeneous effects of taxes on investment behavior by firms. Auerbach, Hines, and Slemrod (2007) provide an analysis of, and recommendations for, corporate taxation in the U.S..

Our work is also related to a number of recent studies that analyze the effects of state-level business and corporate taxation. Serrato and Zidar (2016) study the incidence of state corporate tax changes on firm owners, workers, and landowners using a spatial equilibrium model and find that each of these groups bears, respectively, 40, 30-35, and 25-30 percent of the burden. Fajgelbaum, Morales, Serrato, and Zidar (2016) study the misallocation costs of state-level taxation and find large welfare gains from eliminating spatial dispersion in taxes. Giroud and Rauh (2017) use establishment-level data to estimate the effects of state taxes on business activity (employment and the number of establishments). Again, all these papers use data from recent time periods.

Since we study the location choices of inventors and firms across states in response to taxation, our paper contributes to a recent literature studying migration decisions. Kleven, Landais, Saez, and Schultz (2014) find very high elasticities of the number of high income foreigners in Denmark using a preferential tax scheme on high-earning foreigners implemented by Denmark in 1992 that reduced top tax rates for 3 years.[4] Kleven, Landais, and Saez (2013) study the migration of

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[4]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 U.S. using administrative data.

football players across European clubs. Most closely related, Akcigit, Baslandze, and Stantcheva (2016) study the international mobility of top inventors in response to top tax rates since the 1970s and find significant, but small elasticities. Bakija and Slemrod (2004) use Federal Estate Tax returns to show that higher state taxes on wealthy individuals only narrowly impacts migration across U.S. states.[5] Moretti and Wilson (2014) and Moretti and Wilson (2017) study the effects of state taxes on the migration of star scientists across U.S. states and also finds highly significant effects of taxes on migration.

A key advantage of our new historical datasets is that they provide the opportunity to look at a series of variations in taxes over time and states and to study the effects of taxation systematically. In that sense, our work is also related to the recent public economics literature endeavoring to build detailed long-run datasets of important economic outcomes, such as Piketty and Zucman (2014) and Saez and Zucman (2015) on wealth in the United States and other countries, and Smith, Yagan, Zidar, and Zwick (2017) and Cooper et al. (2016) on who owns wealth and businesses.

Turning to the innovation literature, in endogenous growth models (Romer, 1990; Aghion and Howitt, 1992; Akcigit, 2017; Aghion et al., 2014) innovation is the central engine of growth. How innovation is affected by taxation is a key question because of the many positive social spillovers that innovation induces (Klenow and Rodriguez-Clare, 2005). Bloom et al. (2013) quantify the size of spillovers – positive and negative– of one firm's technological developments in relation to other firms that also engage in innovation.

A related strand of this literature studies the effects of policies like R&D tax credits on innovation revealing a positive impact of these incentives on the level of R&D intensity over both short and longer time horizons (Bloom et al., 2002; Bloom and Griffith, 2001). On the other hand Goolsbee (2003) and Goolsbee (1998) argue that R&D tax credits mostly push up workers' wages. Using a regression discontinuity design based around firm size cutoffs for R&D tax subsidies in the UK, Dechezleprêtre et al. (2016) find a significant effects of subsidies on both R&D spending and patenting. Some research has been undertaken on the recent issue of patent boxes and the shifting of intellectual property to lower corporate tax havens (Griffith et al., 2014; Alstadsæter et al., 2018). All these papers also focus on modern data.

Our work is also related to papers studying the origins of innovation at the micro-level. Recent contributions include Jones (2010) and Jones and Weinberg (2011), which show the effect of inventor age, Jones et al. (2008), which focuses on collaborations of inventors across universities, Wuchty, Jones, and Uzzi (2007), which considers the role of team production, and Jones (2009) on the growing trend towards specialization. Aghion et al. (2017) study the social origins and IQ of inventors in Finland. Bell et al. (2017) and Akcigit et al. (2017) study the parental backgrounds of inventors in the U.S. on, respectively, modern data and historical data.

Our paper is complementary to all these literatures but it is also distinct because it uses newly collected data to examine the role of taxation in the individual innovation process of both firms and

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

inventors. We focus much more broadly over a long time period and on the multitude of innovation outcomes (quantity, quality, and location) that arise from inventor-level and firm-level behavior.

The remainder of the paper is organized as follows. Section 2 describes the source datasets and our data construction. In Section 3, we document historical patterns of innovation and taxation over the 20th century. Section 4 repeats this exercise for patterns in personal and corporate taxation. Section 5 presents our conceptual framework underlying the relationship between taxation and innovation. Section 6 explains our macro state-level estimation strategies and presents our results. Section 7 explains the identification strategies at the individual firm and inventor levels and discusses our micro-level findings. Section 8 concludes with some thoughts about the implications of our results and future research avenues.

2 Data Sources and Construction

In this section, we describe the sources for and the construction of our three new datasets. All the variables constructed from the raw data and used in the figures and tables are defined sequentially throughout the text. Appendix A.1 provides the definitions of all the variables used in full.

2.1 Historical Patent Data and Inventor Panel Data

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

The contribution of the current paper relative to AGN is to transform these patent data into an inventor-level panel dataset. To do so, we disambiguate the data using the machine learning algorithm of Lai et al. (2014). The full algorithm is described in Online Appendix OA.1 and we provide a basic outline of the algorithm below.

The challenge of disambiguating inventor records – determining if two inventors named "John Smith" are the same or not, for instance – may be expressed as a clustering problem. Given a set of patent records, the researcher must ascribe some probability that the two records originate from the same inventor. To do so, we use information on the inventor's name and location, as well as the patent's technology class, set of coauthors on the patent, and assignee. It is very likely that

two records that share the same inventor name, technology class, and location were originated by one inventor. However, it is less likely that two inventors, both named John Smith, were the same individual if one built computer chips for IBM in New York and the other created new packaging for Kraft foods in Illinois.

The starting point for this disambiguation is a well-specified training set. In order to match the work of Lai et al. (2014) as closely as possible, we draw a set of known matches and non-matches from their original disambiguation on modern patent data to form a training dataset. From this dataset, we can compute the likelihood that two records with a given similarity profile are a match. To preserve computational feasibility, we then block records into groups of possible matches, based on inventor names. Finally, we calculate similarity profiles for each pair of records within a block, and compute the posterior probability that two records are a match using our training dataset. A pair of records is considered to be a match if this posterior probability is over 99%.

Table 1 compares the performance of our disambiguation algorithm with that of Lai et al. (2014). Our disambiguation algorithm produces 4.9 million unique inventors, in our dataset of 6.4 million patents. Considering only patents granted to inventors based in the U.S., we observe 2.7 million inventors on 4.2 million patents. Finally, restricting attention to U.S. inventors in our principal sample period of 1940 to 2000, we see 1.95 million inventors and 2.8 million patents.

Our version of the algorithm finds slightly more unique inventors when applied to the Lai et al. (2014) dataset than did the Lai et al. disambiguation. Considering the roughly 4 million patents granted to individuals around the world in the Lai et al. (2014) data, we find 3.3 million unique inventors, compared with the 3.0 million inventors that they find. Similarly, we find 1.6 million inventors in the Lai et al. (2014) data of U.S. inventors, compared with 1.5 million for the Lai et al. (2014) disambiguation. This discrepancy comes from two sources. First, using additional information on historic inventors may lead to slightly different matches in the modern period. Second, we differ slightly in our handling of middle names, by giving additional match probability to record pairs for which one inventor lists his full middle name, and another who lists just his middle initial.

Finally, we supplement these patent microdata with the full matrix of patent citations from 1947 through 2010, which we use to construct a measure of patent quality. Due to well-known challenges in interpreting raw citation counts as patent quality, we adjust patents' citation counts following the quasi-structural procedure laid out in Hall et al. (2001). In brief, this approach assumes that i) the shape of the citation lag function is independent of the patent's total quality, and ii) this lag function is stationary over time. Under these assumptions, one may adjust raw citation counts so that the mean adjusted citation count is constant over time by estimating a simple log-linear regression. Citations received from patents granted in periods with a lower-than-average citation propensity will be over-weighted in the adjustment, as will the citation counts of patents granted at the beginning and end of the period, which particularly suffer from the truncation of our sample

at 2010.[6]

2.2 R&D Lab Data

Our second new dataset consists of information on the R&D activities of firms in the U.S. since 1921 based on National Research Council (NRC) Surveys of *Industrial Research Laboratories of the United States* (IRLUS). This is an extensive and well-documented source of R&D data covering private and publicly-traded firms. For example, Mowery and Rosenberg (1989) wrote about the rise of U.S. R&D based on the early surveys. Our contribution is to utilize information from *all* the surveys. We hand-entered data on all firms included from the 1921, 1927, 1931, 1933, 1938, 1940, 1946, 1950, 1956, 1960, 1965 and 1970 IRLUS volumes.

The NRC was established in 1916 to advise the government on science and technology. Government officials wanted to know where laboratories and scientists were located during the First World War, and R&D became a topic of policy interest due to the rise of in-house R&D during the 1920s. This momentum to collect data carried on for most of the twentieth century. To collect this data, the NRC undertook direct correspondence surveys with firms and sent firms questionnaires. The resulting IRLUS volumes contain the firm-level summary data responses. Figure 1 shows an example entry about the Polaroid Corp. – the innovative Massachusetts-based instant photography firm – and the type of information one can read in each record.

Our R&D data contains several research input-based measures: the total number of research workers employed at each firm and the number and location of R&D labs for each firm. The data are mostly at the firm-level, with limited breakdowns of aggregates at the establishment-level. There are no innovation output-based measures *per se* in the IRLUS surveys. To obtain such output-based measures, we hand-linked R&D firms listed in the IRLUS volumes to assignees in U.S. patent records. The resulting dataset is analogous to the link between the NBER patent database and firms in the Business Register of the Census Bureau for the post-1975 years. It thus provides a valuable historical, long-run counterpart.

2.3 Historical Tax Data

Personal Income Tax Database

We use personal income taxes at both the state and federal level provided by Jon Bakija. These data contain the statutory marginal tax rates and brackets for each state from 1900 through 2014. The data on federal taxes come from the IRS Statistics of Income *Individual Income Tax Returns* publication, while state tax data were collected from a mix of state income tax forms, and state tax laws from the state's "annotated statutes," sourced from the Lexis-Nexis legal research database, and the law libraries at Georgetown and Cornell Universities. Bakija (2017) details the full set of tax rate sources, and attempts to verify their veracity.

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[6]See Akcigit et al. (2017) Appendix B.1 for a detailed description of the adjustment procedure for our historical data. Alternative specifications of the citation lag function did not qualitatively change our results.

3004. Polaroid Corp., 730 Main St., Cambridge 39, Mass. (C*p*)

Research staff: Edwin H. Land, President and Director of Research; Robert M. Palmer, Manager, College Personnel Relations; 50 chemists, 5 engineers, 1 mathematician, 9 physicists, 90 technicians, 18 auxiliaries.

Research on: One-step, three-dimensional, and color photography; color vision; chemistry of photographic processes; polarized light; polymers; absorption of light; organic chemistry; physics and crystallography, especially as related to phenomena involving radiation; spectroscopy; electronics.

Notes: The image shows an example entry from the NRC's publications "Industrial Research Laboratories of the United States." The data was hand-entered based on such entries for all the years available: 1921, 1927, 1931, 1933, 1938, 1940, 1946, 1950, 1956, 1960, 1965 and 1970.

Bakija (2017) also provides a tax calculator program, which models the personal income taxes faced by individuals with income y in state s in year t, after incorporating federal tax deductibility, and other considerations. We use this tax calculator to produce marginal and average tax rates for single filers at the 50th, 75th, and 90th percentiles of the national income distribution.
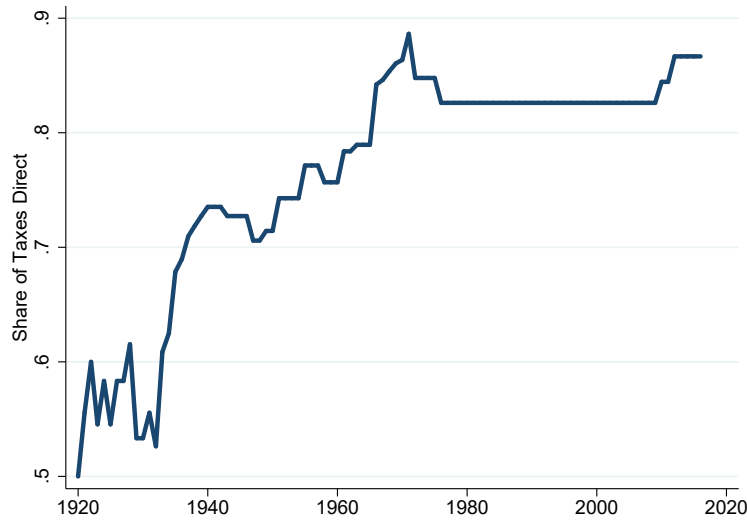
Corporate Income Tax Database

The third dataset consists of a new state-level historical corporate income tax database covering approximately the period 1900-2016. Historically, many states had indirect corporate taxes, such as franchise taxes, imposed on corporations for the privilege of doing business in a state. In several states, statutes make direct taxes unconstitutional and franchise taxes get around this problem. Some states have one or the other, sometimes both, but companies only pay one.

Types of franchise taxes include taxes on net income (which are extremely similar to corporate income taxes and which we consider as such), Business enterprise tax (in New Hampshire), Gross receipts tax or commercial activity tax (which is the gross receipts tax in Ohio), Business and occupation tax (West Virginia, Washington, or Ohio, sometimes different for different industries), net worth/capital stock/asset value/shareholder equity combination taxes, or a value-added tax (Michigan's single business tax which is a franchise tax, not a sales tax). Over time, the share of states with direct corporate income taxes rather than indirect taxes has increased (see Figure 2).

We collect all corporate income tax rates (brackets and rates, if applicable), net income franchise taxes when applicable (since they are very similar to corporate income taxes), as well as any

FIGURE 2: SHARE OF STATES WITH DIRECT (INSTEAD OF FRANCHISE) TAXES

temporary surtaxes and surcharges levied on net income. In addition, we have information on whether a state adopts the same tax base as the federal government for the corporate tax and whether federal corporate income taxes are state deductible. There are differences in the taxable base across states which are almost impossible to capture in a tractable way for the empirical analysis. We instead test that our results are all robust to excluding the set of large states which have a taxable income base that is too different, namely, Michigan, Texas and Ohio. All our results excluding these states are available on demand.

The corporate tax data is collected from a multitude of sources, including detailed State Tax Handbooks and Legal Statutes. For example, we use HeinOnline Session Laws, HeinOnline State Statutes, ProQuest Congressional, Commerce Clearing House (State Tax Handbooks, State Tax Review), State Tax reports, Willis Report, Council of State Governments Book of States, and National Tax Association Proceedings. These sources are described in greater detail in Online Appendix OA.3.

3 Inventors, Firms, and Innovation in the 20th Century

3.1 Inventors

Table 2 provides some key summary statistics about inventors. The average inventor appears in the patent data for 3 (not necessarily consecutive) years, but a top 5% inventor remains for 14 years and a top 1% inventor for 31 years. On average, inventors remain in the same state, but the most mobile inventors appear in 3 states over their careers. The number of patents per inventor is

also highly skewed, ranging from 2.55 patents for the average inventor to 26 patents for a top 1% inventor. Even more concentrated are citations, an often-used marker of quality of an innovation (Hall et al., 2001; Trajtenberg, 1990). The total citations of a patent are all the citations ever received by this patent, subject to the adjustment described in Section 2. The average inventor receives 83.42 citations for his patents, but a top 1% inventor receives 1189.25 over the course of his career, and gets up to 329 citations per year. Inventors also frequently work in multiple fields: the average inventor has patents in close to 2 USPTO technology classes and a top 1% inventor in 14 classes.[7]

Figure 3 shows the geography of innovation since 1940, by depicting patents per capita at the state level for each decade. In all our analysis, the year t of a patent will be counted as the application date. This ensures a shorter time interval between a tax change and an innovation outcome and is most indicative of when an innovation was actually created, as opposed to granted. The North East Coast, the Chicago area and California appear as major hubs early on. Patents per capita do not increase monotonically through time, and the 1970s recession can be observed here too. In the 1990s and 2000s there is a large increase in patents per capita everywhere and an expansion of innovation regions.

Figure 4 shows the share of corporate inventors and patents over time. Corporate patents are those patents assigned to corporations. Corporate inventors are defined here as inventors who have at least one corporate patent in their career. Both shares have fluctuated, but increased significantly over time.

3.2   R&D Labs

Figure 5 shows maps of the location of R&D labs for each of the IRLUS survey years. R&D labs in 1921 were few and almost exclusively located on the East Coast and in the Midwest. Over time, labs spread West to populate parts of the Midwest and clusters of labs appear in California, specifically Los Angeles and San Francisco. As labs became more numerous, several hubs appeared in places like Pittsburgh, Cleveland and Detroit, and more generally the northeastern part of the country where the U.S. "manufacturing belt" emerged (Krugman, 1991).

Figure 6 shows trends in R&D labs' operations over time. Panel (A) shows that the total number of labs is steadily rising until 1960, but stagnated thereafter until 1970 (the last year of the IRLUS). Panels (B) and (C) show that the trend in patents and citations produced by these R&D labs also trends upwards between 1920-1965, but then shows a clear decline post 1965. There are momentary spikes of activity around 1930 and 1950. The 1930s witnessed one of the most innovative decades in American history, despite the Great Depression (Field, 2003), while innovation in areas like radar detection and aviation was spurred by the potentially transformative effects of heightened R&D

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

investment during the Second World War (Gordon, 2016).

Further analysis of Figure 6 shows the number of research workers increases sharply from less than 20,000 in 1920 to close to 500,000 in 1965, and then falls back to 300,000 in 1970. Research workers per lab also increase from less than 10 per lab in 1920 to 100 per lab in 1965 and declines back to 58 per lab in 1970. These changes are consistent with the historical context. Griliches (1986) notes that corporate R&D activity peaked during the late 1960s, with R&D expenditures relative to sales falling by about 38% between 1968 and 1979. From late 1969 through much of the mid-1970s the United States experienced one of the most significant recessions in its history.

We next present statistics about the innovation behavior of firms, represented in Figure 7. Panel A shows the share of firms with at least one patent, which are listed in the IRLUS volumes, for every year that these volumes exist. The share has declined over time. Panel B shows the distribution of patents per year and per firm, conditional on patenting and being in the R&D lab registry, in the full sample. The share of firms which have at least one patent in a given year is 22%. The distribution exhibits a large mass of close to 35% at 1 patent. The median firm-year has 3 patents, conditional on having any, and the mean is 10.3. The distribution is right-skewed with 1% of firm-years having more than 20 patents. Panel C plots, for all years since 1920, several percentiles of the distribution of patents per firm per year such as the median or the 99th percentile. Note that we do observe patents for every year, even for the years in between the IRLUS surveys. The median and 75th percentiles remain relatively constant over time, with some fluctuations. The number of patents for firms in the top 10% and above has increased. Thus, the distribution has become more skewed over time, with top firms increasingly accounting for more of total patenting activity.

4   Personal and Corporate Income Taxation in the 20th Century

In this section, we describe some key facts about personal and corporate income taxes over the 20th century. Because the corporate income tax database is newly collected and crucial to the analysis, we devote some extra space to discuss corporate tax patterns.

4.1   Personal Income Taxes

Figure 8 shows the first year in which state personal income taxation was introduced in different states. The first states to introduce personal income taxes were Virginia and South Carolina in 1900, followed closely by North Carolina and Hawaii in 1902, Oklahoma in 1908, Wisconsin in 1911, and Mississippi in 1912. The last states to adopt an income tax were Rhode Island, Maine, Illinois, and Connecticut (all in 1969), Pennsylvania in 1971, Ohio in 1972, and New Jersey in 1975. However, the first year of introduction is not necessarily reflective of the relevance of taxation for most, or even, many individuals in the state. State taxes initially mostly applied to top earners. For this reason our analysis will focus mostly on the post-1940 period.

Figure 9 shows in Panel (A) that the number of states with a personal income tax increases sharply between 1920 and 1940, stagnates until the 1970s, during which time a number of additional states adopted a personal income tax, before the number flattens out towards the end of the time period. The mean non-zero tax at the state level has followed a shape not dissimilar to the Federal top marginal tax rate: rising in the 1950s until the 1980s, and declining thereafter. Panel (B) shows some additional features of the distribution of top personal income taxes across states. It depicts for each year, the 25th percentile, the mean, the median and the 90th percentile of the personal top tax rate distribution across states in that year. In the 1920s and 1930s, the top tax rate in the median state was zero and only became positive in the 1940s. In the late 1960s, the top tax rate became positive even in the 25th percentile state. All above median states saw their top tax rates increase until the 1980s and decline thereafter. The most progressive states' top tax rate reached 16% in 1980.

Many states have progressive tax systems, even though they are typically much less progressive than the Federal system. States with progressive taxes are California, New York, and New Jersey. Some states instead have flat taxes, e.g., Connecticut, Massachusetts, and Illinois.

Construction of the Tax Measures

At the state level, there have been many, frequent personal tax changes, as illustrated in Panel (A) of Figure 10 which shows the number of states altering the statutory marginal tax rate faced by the top or median earners in any given year. There is a spike in tax changes in the 1980s and early 1990s. Panel (B) shows that changes in tax rates are also accompanied by changes in the tax brackets, although it is especially the top tax bracket that has moved a lot over time. States typically have few tax brackets so that the top tax bracket is particularly defining.

Because of these frequent changes in the tax brackets, for the analysis, we compute the 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. We use Jon Bakija's calculator, which takes into account special rules and deductions. We compute marginal and average tax rates. We refer the reader to Bakija (2017) for more details.

Our tax measures, which focus on the tax liability at a given (relative) point in the income distribution, take into account changes in the tax brackets and thus measure the total impact on individuals at different parts of the income distribution. To summarize, our tax variables used throughout will be:

- the 90th percentile income MTR

- the 90th percentile income ATR

- the median income MTR

- the median income ATR

Figure 11 shows the evolution of the marginal tax rate at the median income level decade-by-decade and Figure 12 shows the same for the marginal tax rate at the 90th income percentile.

Figure 13 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. Panel A, shows that state top tax rates have followed very different trajectories – and have also evolved differently from the federal tax rate – in these states. California had a very high top tax rate in the 1930s, before lowering it sharply after 1940. Since then, the top tax rate has slowly increased and fluctuated around 10%. New York had a much lower top tax rate until the mid-60s, which increased sharply to around 15% until the mid-80s; it has since decreased to around 7-8%. Illinois and Pennsylvania have had low and stable flat taxes since the late 60s. New Jersey introduced its tax relatively late and it has fluctuated considerably since. The right panel illustrates the evolution of tax rates at the median income level in these same states. Here, the time patterns are much more similar across states, although the levels are different. In all states, the tax rates increase over time until the 1980s and then either remain relatively flat (as in New Jersey, California, Pennsylvania, and Illinois) or decrease as in New York.

4.2 Corporate Income Taxes

Our measure of state-level firm taxation will be the top corporate marginal tax rate. In our regression analysis, we will compute the total tax rate of a firm by taking into account the top federal corporate tax rate and the state and federal tax deductibility rules.

Figure 14 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). Panel (A) of Figure 15 shows the number of states with a corporate tax, which increases sharply and then flattens completely after 1972, as well as the mean state tax (conditional on having one) which increases from around 3.5% in 1920 to close to 8% in the 1990s, and has declined slightly to above 7% since then.

Panel (B) provides more details on the distribution of state corporate taxes in each year since 1920. The top 10% states ranked according to corporate taxes saw their corporate tax rise from 2% in 1920 to around 10% today. The lowest 25% states never had a tax rate above 4%. The median state had a corporate tax only since the late 1930s and it hovers around 6% today. Another feature of this graph to notice is the increasing dispersion over time. In 1920, corporate taxes in the lowest tax states were 0% and in the highest states were just around 2%. In the mid-century, the dispersion had increased from 0 to 6% and it reached 0 to 10% in the 2000s.

Panel C shows the evolution of the top corporate tax rate in a few select states with different experiences. California and New York were one of the relatively early adopters of a corporate tax and have followed similar patterns, with tax rates rising continuously before 1980, and experiencing

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stagnating levels thereafter. Pennsylvania, another early adopter, followed a broadly similar pattern, but with more spikes in specific years. New Jersey was one of the late adopters but quickly brought its tax rate up to the same level as California, New York and Pennsylvania. Illinois also adopted a corporate tax quite late and kept it at a low and stable rate of close to 5% over time.

Finally, Figure 16 shows the evolution of the top corporate tax rates in all states, decade by decade.

Apportionment Rules

We briefly discuss apportionment rules for multi-state firms and how they affect our results. In our sample only around 6.5% of firms are multi-state in the sense that they have an R&D lab in more than one state at a given time. Before the Uniform Division of Income for Tax Purposes Act (UDITPA) in 1957, different states had different ways of dealing with the taxation of multi-state companies. The UDITPA made these apportionment and allocation rules of the business income of multi-state companies more uniform, with a three-factor formula based on equal weights to the shares of a corporation's payroll, property, and sales in the state, although not all states adopted it. In the past twenty years, the weight on sales has started to increase, which should arguably decrease the importance for a company of corporate income tax in states in which it has property and employment (but a low share of its sales). We do not have information on the three factors entering the apportionment formulas for the firms in our sample. Also firms which have an R&D lab in only one state may still have a corporate tax nexus in other states.

We simply use as a measure of the tax rate the corporate income tax prevailing in the state where the firm has its R&D lab, and, when a firm has R&D labs in multiple states, we use the average corporate tax weighted by the share of labs in that state. The estimated effect in our regressions is likely to be a lower bound of the true effect of corporate taxes because the measure of the corporate tax we use is exactly equal to the true tax rate facing single-state firms (i.e., firms which have tax nexus only in one state), and positively correlated with, but not exactly equal to the true tax rate facing multi-state firms. At one end of the spectrum, if all the apportionment weight was on the sales factor, and no sales happened in the state where the R&D labs are located, we should estimate a zero effect of corporate income taxes in that state. At the opposite end, if firms have a nexus only in the state where their R&D lab is located, the corporate tax of that state is the one that matters.[8] In between, the higher the share of the firm's sales, property, and employment in the state where its R&D lab is located, the closer the estimated effect of the corporate income tax should be to the true effect.

Other taxes: Discussion

Although not the focus of our paper, which concentrates on corporate and personal income taxation, alternative methods of taxation exist as potential confounding factors, which may pollute our

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[8]Of course, when it comes to location decisions, as we will explore in Section 7, the tax rates of all states matter.

estimates if they are not adequately taken into account. Therefore, it is worth considering how these alternative taxes may impact our proposed identification strategies, as described in the introduction and detailed below. Capital gains taxes may matter; however, ordinary capital gains (non long-term) 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 form 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 × year fixed effects. In any case, it is also not evident that the long-term capital gains rate is more relevant than the short-term one. Dividends are typically taxed as ordinary income at the Federal level and in most states; they are thus again captured by our personal income tax measures. States' sales taxes are absorbed by our state × year fixed effects. Property taxes are exceedingly complicated to collect historically and are too diverse and local to lend themselves to a study in our setting. This would be a potentially fruitful, although difficult, avenue for future research.

To summarize, our fixed effects absorb these residual tax variations. In addition, our instrumental variable strategy results are robust to omitted variables – not only taxes. In any case, as we will show below, our various identification strategies yield very consistent results.

5 Conceptual Framework: Effects of Taxes on Innovation

What are the possible channels through which the taxation of personal and corporate income can affect innovation by firms and individual inventors? A very simple static model helps to fix ideas. The goal is to show that there are several margins of responses to taxes and that their magnitudes need to be determined empirically. We discuss the factors that affect the strength of these margins of responses, as well as what is captured in our regressions at the micro and macro levels.

Simple Static Model of Innovation

Suppose that inventor i has decided to live in state s with personal income tax rate τ_s^{yi} and corporate tax rate τ_s^c. y indexes personal income taxes; c indexes corporate taxes. The inventor needs to choose how much effort e_i to exert and how many resources r_i (i.e., material innovation inputs, such as R&D expenses, lab space, machinery and equipment, etc.) to devote to innovation. Effort has a disutility cost $h_i(e_i)$ and resources cost $m(r_i)$. Inventors can patent on their own, or can be employed by companies. If the innovation is developed within a firm j, the firm also provides innovation inputs, denoted by R_j. In addition, each state has an innovation infrastructure and economic policy framework, denoted by X_s which can improve the productivity of the private inputs to innovation and/or shift the profits obtained from them.

The quantity k and quality q of the innovation produced depend positively on effort and resources invested by the inventor, as well as by the firm (if the inventor is employed), and on the

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state's innovation policies and resources, with:

$$k_i = k(e_i, r_i, R_j, X_s) \qquad q_i = q_i(e_i, r_i, R_j, X_s) \tag{1}$$

If an inventor is self-employed, his innovation does not depend on the firm inputs R_j.

Inventors receive a private benefit b_i from innovating, due to the "warm-glow" of being success-ful, or from a "love for science." b_i is itself an increasing function of the quality and quantity of innovation produced, with $b_i = b_i(k_i, q_i)$. Let g_i be the weight that inventor i puts on his private benefit and $(1 - g_i)$ the weight on the financial returns from an innovation.

A self-employed inventor can sell his innovation to a producer (e.g., a firm) or can himself start producing a new marketable item based on it. His payoff depends on his innovation quality and the policies and market structure in the state (including the intellectual property protection), which we denote $\pi(k_i, q_i, X_s)$. The inventor can incorporate as a firm or remain self-employed, which means that the innovation can possibly be taxed in different tax bases.

To allow for all possible combinations, suppose that a share β_i^c of that surplus is taxed in the corporate tax base (if the inventor incorporates) and a share $1 - \beta_i^c$ is taxed in the personal tax base (if the inventor keeps being self-employed). These shares are inventor-specific choices.

Note that the share of the payoff that accrues to the personal vs. corporate income base could also be endogenized in response to taxes to capture, among others, income shifting responses. Furthermore, if resource investments into R&D are fully tax-deductible, they would not respond to tax changes. Effort investments are typically hard to make fully tax-deductible. They can also be interpreted more broadly as unobservable R&D inputs (for a discussion of R&D policies when there is asymmetric information and unobservable R&D investments, see Akcigit et al. (2016)).

The self-employed inventor's total payoff is then:

$$V_{is}^{SE} = \max_{e_i, r_i} \left((1 - g_i) \left[1 - (1 - \beta_i^c)\tau_s^{yi} - \beta_i^c \tau_s^c \right] \pi(k_i, q_i, X_s) + g_i b_i(k_i, q_i) - h_i(e_i) - m(r_i) \right)$$

where k_i and q_i are functions of effort and resources as given by (1).

For the sake of the exposition in this conceptual framework, the corporate and personal income tax rates should be viewed as the total rates paid, including for instance, dividend taxes and capital gains taxes. In our empirical analysis, these are controlled for as already explained in detail in Section 4.2.

Inventors can also choose to be employed by firms. In the labor market of each state, firms open one or several vacancies at a cost γ_j per vacancy for firm j, and inventors are matched to firms to fill each of these vacancies. Jointly, inventors and firms produce a gross-of-tax surplus $V(q, k)$ that depends positively on the innovation quantity and quality produced by the match. This surplus is taxed at the corporate tax τ_{st}^c. The firm pays resource costs $M_j(R_j)$ to invest in innovation. Imagine there is Nash bargaining between the firm and each worker with bargaining weight α of

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the worker. Then the wage paid to the worker with outside option (from being a self-employed inventor) V_i^{SE} is:

$$w_i(q, k; V_i^{SE}) = V_i^{SE} + \alpha \left[(1 - \tau_{st}^c)V(q, k) - M_j(R_j) - h_i(e_i) - m(r_i) - V_i^{SE} - \gamma^j \right]$$

and the firm's payoff W_{ij} from being matched to inventor i is:

$$W_{ij} = \max_{R_j} \left((1 - \alpha) \cdot \left[(1 - \tau_{st}^c)V(q, k) - M_j(R_j) - h_i(e_i) - m(r_i) - V_i^{SE} - \gamma^j \right] \right)$$

The value of an employed worker is:

$$V_{is}^E = \max_{e_i, r_i} \left((1 - g_i)(1 - \tau_s^{yi})w_i(q_i, k_i; V_i^{SE}) + g_i b_i(k_i, q_i) \right)$$

Aghion et al. (2018) and Kline et al. (2017) offer recent evidence on how the surplus from innovation is shared between inventors, entrepreneurs/firms, and blue and white-collar workers. The inventor will choose to be self-employed if and only if $V_{is}^{SE} \geq V_{is}^E$.

Responses to Taxation: Even in this simple model, both personal and corporate income taxes enter the payoffs of firms and inventors. There are also several margins through which inventors and firms can affect innovation, all of which can be reflected in responses to taxation:

1. Innovation inputs choices, namely effort e_i and resources r_i, on the intensive and extensive margin. E.g., an inventor can choose whether to work at all and, conditional on working, how much effort to supply.

2. Occupational choices, i.e., whether to be self-employed or employed, or, more broadly, whether to engage in innovation at all.

3. Tax base choices when self-employed, namely the decision whether or not to incorporate or sell the innovation, or to use it as a self-employed agent, as captured by β_i^c.

4. Location choice: the choice of the state s where to locate.

Similarly, there are several margins of response to taxes at the firm-level:

1. Innovation input choices: namely the choice of resource investment R_j for each of their inventors and lines of research, on the intensive and extensive margin (whether to engage in innovation at all).

2. Their research employment, i.e., the number of vacancies to open.

3. Location choice: which state s to locate in.

Based on these margins of responses and the value functions above, we can note the following six effects of taxes.

First, it is not the case that only corporate taxes affect firms or personal income taxes affect inventors; rather personal and corporate income taxes can affect *both* firms and inventors. A self-employed inventor can choose to incorporate or shift some of the income from his innovation to the corporate sector. Thus, whether personal or corporate tax matters more for either a firm or an inventor again will depend empirically on what the innovation is used for and in which tax base the payoffs end up accruing. An employed inventor's return is also affected by the corporate tax due to its effect on the surplus available to share. The same goes for firms: both the inventor and the firm bear some of the incidence of state corporate and personal income taxes. Put differently, the firm does not entirely pay the inventor a compensating differential to buffer against a higher personal income tax, and, conversely, the firm does not fully insulate the inventor against fluctuations in the corporate tax either.[9]

Second, the responses to taxation are shaped by technological parameters, such as the elasticities of innovation quality and quantity to effort and resource costs by agents and firms. For instance, it may be that quantity is very sensitive to inputs, but that quality is not. Does one just "stumble" upon innovations of a given quality or do they require consistent and intentional inputs?

Third, the strength of the responses to taxes along all the aforementioned margins may vary and their magnitudes are empirical questions. One can come up with many instances of forces pushing towards stronger effects of taxes on innovation, but also with many examples of forces dampening the effects. Consider a few examples. How elastic the innovation inputs – effort and resource investments – are to net returns and, thus, to taxes, will depend on how strongly innovators value the private warm-glow effect relative to financial returns. One can imagine two polar scenarios. In the first scenario, ideas either happen without any willful input (such as for Newton sitting under a tree and discovering gravity from an apple falling), or the inputs required to produce them are completely inelastic to net returns (as the stereotype of the "mad and passionate scientist" would predict). In these cases, there would be no response of innovation to taxation at all. In the second scenario, innovation requires intentionally directed inputs and those inputs are sensitive to net returns. We would then expect stronger responses of innovation to taxes. For firms, the strength of a response of innovation inputs to taxes will depend on the extent to which these research expenses are tax-deductible (if all inputs without exception are perfectly tax-deductible, taxation does not affect the optimal investment in innovation). Firms' responses to taxation will also depend on whether innovation is financed out of retained earnings.

Fourth, one may expect corporate and non-corporate inventors to be quite different in terms of their responses to taxes for many reasons. Corporate inventors are naturally more exposed to the corporate tax rate, although both types of inventors are exposed to the personal tax rate. In addition, these two types of inventors may have very different weights on the financial returns

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[9]This is generally true, except in the special case in which the inventor's bargaining power is zero, or if there is a perfectly competitive frictionless market.

versus private benefit. Furthermore, the sensitivity of an inventor's wage to his innovation output depends on the bargaining structure and his bargaining weight. And the outcome of innovation at the firm-level depends on the joint inputs of firms and inventors, each of which react to taxes in a different way.

Fifth, on the location choice and cross-state mobility margin, we would expect no responses to differential taxation across states if it is difficult to move across states, or if other factors completely dominate the location choice decision. One such factor is the home-state bias, i.e., that inventors simply prefer living in their home state. Another such factor may be agglomeration. One may choose to trade-off a higher tax in favor of remaining in a place with more inventors in general or more particularly in one's field. These agglomeration effects may enter the production function directly through X_s and improve the productivity of any given innovation input.

Sixth, taxation can have general equilibrium effects, as embodied in the variables $\mathbb{X}_s$.[10] More taxes also yield more government revenues, which can foster investments in infrastructure and environments for innovation, such as better schooling or better communication systems. While interesting *per se* and very complicated to model, these effects are controlled for in our regressions by detailed state-year, firm, technology class controls and their interactions (often state-year fixed effects).

Finally, it is important to emphasize that this simple framework is static, but the effects of taxes on innovation are in reality dynamic. For instance, taxation may affect innovation with some lag. The strength of its effects also depends on whether a given tax change is considered to be short-lived or more persistent. These are common issues for empirical studies of taxation and are not specific to the relationship between taxes and innovation itself.

What is measured at the individual inventor and macro levels? At the individual inventor level, some of these response margins are directly observable, such as the inventor's occupational choice (whether he is an employee or not), and his state choice. Some other outcomes' responses, however, capture composites of these various response margins. For instance, when regressing the number of patents at the individual inventor level on personal and corporate income taxes in a given state, the response observed can be the result of an inventor changing his work effort (the usual "labor supply" elasticity) or investment of resources, shifting between the corporate and personal tax bases, or extensive margin responses of engaging in innovation at all. These estimates are not "primitive" parameters in the sense of being directly mapped to utility parameters, but importantly they do capture the reduced-form individual-level responses.

At the macro state-level, the total responses measured are the result of both firms' and inventors' responses, and across all the margins, intensive and extensive. In addition, they also capture movements across states. One may thus wonder whether the responses to taxes are pure zero-sum effects. Do states simply attract resources from other states when they lower their taxes? We directly test for such cross-state spillovers and business-stealing and find that while important,

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[10]It may have spillover effects not only within-state, but also across states.

they do not explain the full effect at the state level.[11]

It is worth noting that some caution is needed to extrapolate the individual-level responses in order to understand what may happen if there is a federal tax change. A nation-wide tax change may create further general equilibrium ramifications. Nevertheless, given the detailed controls in our regressions, the estimated elasticities are informative about people's responses to tax changes or the net returns in general.

To sum up, there are several margins through which firms and individual inventors (corporate, non corporate, or a mix of the two) can be affected by both personal and corporate income taxes. Their decision margins concern how much innovation inputs to supply, where to locate and whether to participate in the innovation process at all. These theoretical effects should be observable in the data with respect to the quantity, quality, and location of innovation. We now turn to testing the magnitudes of these margins empirically.

6   The Macro Effects of Taxation

We begin with the effects of personal and corporate taxes at the macro, state level. We focus on the period 1940-2000. Let us denote by τ_{st}^{c} the corporate tax in state s year t and τ_{st}^{yj} the personal income tax at income percentile j in state s in year t. Let the corresponding federal level tax rates be τ_{ft}^{c} and τ_{ft}^{yj}. Following the reasoning from Section 4, 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. We focus on two income percentiles: the 90th percentile and the median.

In a heuristic way, ignoring the many 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 T_{st}^{yj} and is equal to:

$$T_{st}^{yj} = \tau_{ft}^{yj}(1 - \tau_{st}^{yj}) + \tau_{st}^{yj} - D_{st}^{y} \cdot \tau_{st}^{yj}\tau_{ft}^{yj} \tag{2}$$

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

$$T_{st}^{c} = \tau_{ft}^{c}(1 - \tau_{st}^{c}) + \tau_{st}^{c} - D_{st}^{c} \cdot \tau_{st}^{c}\tau_{ft}^{c} \tag{3}$$

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[11]In addition, the individual-level responses show that inventors respond also by changing their innovation quality and quantity, and not just by moving across states. There could be additional business-stealing effects from other states due to market size and the demand side.

In this section, we estimate the following type of equations:

$$Y_{st} = \alpha + \beta_y T^{yj}_{st-1} + \beta_c T^c_{st-1} + \gamma \mathbb{X}_{st} + \delta_t + \delta_s + \varepsilon_{st} \tag{4}$$

where Y_{st} is some innovation outcome in state s in year t. Our outcomes will be, for each year and state, the number of patents produced during that year in the state, the number of total citations to the patents produced in the state, the number of inventors living in the state, the number of "superstar" inventors, average citations per patent, and the share of patents assigned to companies. T^{yj}_{st-1} is the lagged personal income tax rate (average or marginal) for income group j (median or 90th percentile) in state s and T^c_{st-1} is the lagged corporate tax rate. δ_t and δ_s are sets of year and state fixed effects. $\mathbb{X}_{st}$ are time-varying state-level controls, namely, lagged population density, real GDP per capita and, importantly, R&D tax credits. The latter controls for other targeted, time-varying incentives for innovation. Throughout, we weight each state by its concurrent population.[12]

As explained in Section 5, at the macro level, the effect of each tax is its total effect on both firms and inventors and represents a mix of extensive margin responses (e.g., inventors or firms moving across states, or entering and exiting the innovation market) and intensive margin responses (e.g., inventors choosing how hard to work on their research, or companies choosing how many researchers to hire). The fact that state level outcomes are the result of a mix of intensive and extensive margin responses is also the reason why we consider both marginal tax rates (MTR), which matter for intensive margin responses, and average tax rates (ATR), which matter for extensive margin responses. At the macro-level, part of the total tax effect measured could be "business-stealing" effects, whereby if one state lowers its taxes, it merely attracts innovation from other states without a resulting increase in overall U.S. innovation.

6.1 OLS Results

Table 3 shows the estimates from state-level regressions where the tax measures are, as described above, total tax rates, include the federal tax rate and take into account the fact that different states have different rules for deductibility for federal taxes. The unit of observation is a state-year. Each of the four horizontal panels shows coefficients from a regression of the dependent variable in each column on a different measure of the personal tax rate burden and the top corporate tax rate. The four panels focus, respectively, on the effects of the marginal tax rate (MTR) at the 90th percentile income, the MTR at the median income, the average tax rate (ATR) at the 90th percentile income, and the ATR at the median income. The corporate tax measure is always the top corporate tax rate. All taxes are measured in percentage points and are lagged by one year.

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[12]We choose not to study innovation per capita as our baseline dependent variables due to concerns over endogenous migration. The development of innovation hubs is likely to lead to fast local population growth, which is a relevant consideration for policymakers. In unreported results, we find a qualitatively similar effects of taxes on innovation per capita - higher taxes for both individuals and corporates tend to reduce per capita patents, citations, and inventors.

All regressions at the state-year level include controls for lagged population density, real GDP per capita, R&D tax credits, as well as state and year fixed effects.

The table's columns show the effects of taxes on log patents, log citations, log inventors, log superstar inventors, citations per patent and the share of patents assigned, i.e., granted to a company rather than to an individual. Superstar inventors are defined as inventors in the top 5% of the patent count distribution in year t, where the patent count at time t is an inventor's total patents up to and including $t-1$. Recall that a patent's citations are all the forward citations ever received by a patent, subject to the adjustment described in Section 2. Citations of a state in year t are thus the total citations received by patents that were applied for in state s in year t. Appendix Table A1 replicates these results using only statutory state-level taxes. The results are very similar.

All the tax measures – personal and corporate – are significantly correlated with lower patent counts at the state level. A one percentage point increase in either the median or top marginal tax rate is associated with approximately a 4% decline in patents, citations, and inventors, and a close to 5% decline in the number of superstar inventors in the state. The effects of average personal tax rates are even larger. A one percentage increase in the average tax rate at the 90th income percentile is associated with a roughly 6% decline in patents, citations, and inventors and an 8% decline in superstar inventors. For the average tax rate at the median income level, the effects are closer to 10% for patents, citations, and inventors, and 15% for superstar inventors. Citations per patent do not exhibit a very systematic response to taxes at the macro level, which is self-evident given that citations and patents seem to react very similarly to taxation at the macro levels. The macro elasticities to marginal tax rates implied by these coefficients are between 2 (for the MTR at the 90th percentile income) and 3.4 (for the MTR at the median) for patents, inventors, and citations. A one percentage point higher top corporate tax rate leads to around 6-6.3% fewer patents, 5.5-6% fewer citations, 4.6-5% fewer inventors, and 8.5-9.3% fewer superstar inventors. The implied macro elasticities are, respectively, 3.5, 3, 2.5, and 4.

The share of assigned patents appears to be very sensitive to the corporate tax rate. A one percentage point increase in the top corporate tax rate is associated with close to 1.2 percentage points fewer patents assigned to companies. In fact, taxes tend to decrease both corporate and non-corporate patents, but corporate patents more so, leading to a decline in the share assigned. The share assigned is also negatively related to the personal income tax rate. This is perfectly in line with our findings at the micro level in Section 7, because it shows that corporate inventors are systematically more sensitive to both corporate and personal taxes.

One potential concern is that the effects are sensitive to large, highly-innovative states such as California. Appendix Table A2 shows that this is not the case. Dropping California from the analysis leaves the results substantively unchanged.

6.2 Instrumental Variable Strategy using Federal Tax Changes

One way of better identifying the effects of taxes, is to exploit changes in total personal and corporate tax burdens at the state level, which are not driven by changes in state taxes, but rather exclusively driven by federal tax changes. Our instrument is similar in spirit to the predicted tax burden in Gruber and Saez (2002) or the predicted eligibility in Currie and Gruber (1996). Specifically, the instrument used for the personal or corporate tax in state s at year t is the tax that would apply if the state-level personal or corporate tax rate did not change since year $t - k$ (where k is allowed to vary), but federal taxes were changing as they are in reality. Changes in the predicted tax are therefore driven purely by federal tax changes. The impact of federal tax changes varies by state and by income group based on the level of its state taxes and on whether the state allows for federal tax deductibility.

Heuristically, the instrument for the personal income tax of income group j in state s and year t, denoted by $\hat{T}_{st}^{yj}$, can be written as:

$$\hat{T}_{st}^{yj} = \tau_{ft}^{yj}(1 - \tau_{st-k}^{yj}) + \tau_{st-k}^{yj} - D_{st-k}^{y} \cdot \tau_{st-k}^{yj}\tau_{ft}^{yj} \tag{5}$$

where the actual state tax in year t is replaced by its lag τ_{st-k}^{yj} at time $t - k$, and where we allow k to vary for robustness (the benchmark has $k = 5$). 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 T_{st}^{yj}. Similarly, we instrument the corporate tax rate using the predicted tax burden holding state taxes fixed at their level in year $t - k$ (again, the benchmark is $k = 5$),

$$\hat{T}_{st}^{c} = \tau_{ft}^{c}(1 - \tau_{st-k}^{c}) + \tau_{st-k}^{c} - D_{st-k}^{c} \cdot \tau_{st-k}^{c}\tau_{ft}^{c} \tag{6}$$

Recall that the specification always includes state and year fixed effects.

The results are presented in Table 4. The IV estimates are highly significant and very close to the OLS estimates, albeit slightly larger. One potential explanation for the larger IV estimates is that states are adjusting their tax rates in a counter-cyclical fashion, which would bias the OLS estimates downwards.

6.3 Border Counties Strategy

Our other identification strategy at the macro-level consists of using border counties. Border counties are neighboring counties that lie in different states. Because such counties are located next to each other, they are presumably subject to similar economic conditions and shocks, but not to the same tax policies, since those are set at the state-level.

We start by matching all inventors and patents to their counties and we restrict the sample to neighboring counties across state lines. We then run the following regression:

$$\Delta Y_{it} = \beta_y \Delta T_{it-1}^{yj} + \beta_c \Delta T_{it-1}^{c} + \gamma \Delta \mathbb{X}_{it} + \delta_i + \varepsilon_{it} \tag{7}$$

where i indexes a pair of border counties in two different states, δ_i is a border pair fixed effect, and the Δ operator takes the difference of any variable between the two border counties of a pair. ΔY_{it} is the difference in innovation outcomes between the two counties, which includes log patents, log citations, log inventors, citations per patents and corporate patents. ΔT^{yj}_{it-1} is the difference in lagged personal tax rates (marginal or average) for income group j and ΔT^c_{it-1} is the difference in the lagged corporate tax rates. The set $\mathbb{X}_{it}$ contains lagged population density, lagged real GDP per capita, and an R&D tax credit measure.

Table 5 mirrors Table 3, but restricts the sample to border county pairs, and shows the results of the estimation of (7) with OLS. The estimated effects of personal and corporate income taxes are significantly negative and generally comparable to the benchmark macro results, being somewhat smaller for some outcome and tax combinations, and somewhat larger for others.[13]

We also combine the border county strategy and our IV approach, by instrumenting the tax rate differentials between the border counties with the difference in the instruments $\Delta \hat{T}^c_{it-1}$ and $\Delta \hat{T}^{yj}_{it-1}$ which are defined in (5) and (6). The results are shown in Table 6. The coefficients gravitate around their values shown in either the border county OLS (Table 3) or the macro state IV results (Table 4) and the results are very consistent with the earlier estimates. If anything, the effects of taxes appear even stronger with the combination of border county and instrumental variables strategies.

Overall, the border county strategy, either using OLS or our instrumental variable specification, also confirms that there are significant effects of personal and corporate taxes and that the magnitudes are consistent with the ones found at the macro state-level.

6.4 Cross-State Spillovers and Business Stealing

The macro effects just discussed can be interpreted as the relevant reduced-form effects facing states when considering whether to lower or raise their personal or corporate income taxes, without retaliation from other states. Thus, they are of interest *per se*. These effects may be partially driven by positive or negative spillovers on other states, due to business stealing and to the possibility that factors and demand may shift across state lines. Although potentially valuable to each individual state, these effects do not necessarily represent extra value creation in innovation when aggregated up to the federal level. Consequently it is important to measure the net value creation effects which are not due to business shifting across states. To better understand these net effects, we adopt two approaches.

First, as we will show in Section 7, inventors and firms do relocate in response to taxation and this is an important margin of interest when thinking of the impact of taxes. Therefore, in Table 7, we replicate our core macro IV results, but drop all inventors who ever moved states (Table A3 shows the OLS results). The magnitudes of the effects are only very slightly reduced. We perform

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[13]Throughout our border county analysis, we restrict attention to sufficiently large border county pairs in which both counties have at least 6 patents in a given year. Our results are not sensitive to this choice. We also weight each county pair by its concurrent combined population.

this same exercise of dropping movers from the sample also for the border county pairs from Section 6.3. In fact, movements across states may be particularly strong for border counties. Thus, if the tax effects were mostly driven by movements across states, we would expect the coefficients on taxes to be most reduced by the omission of movers in the border county regressions. The results in Table 8 are very consistent with the baseline border county results.[14] Thus, it appears that the effects of one state changing its taxes are not purely driven by inventors moving across states.

Cross-state spillovers can also arise when other factors (not only inventors) or demand moves. To test for this possibility, we can compare the estimated total border county effect (between the two border counties of a pair) to the change in the same innovation outcome between the border county that did not experience the tax change and the average county in its state. To be more precise, denote the county with the tax change m and n the border county of the same pair, and k the average county in the same state as n. Under the assumption that the difference in outcomes between the border county n and the average county k in its state would have remained constant before and after the tax change, the change in outcomes between these two counties measures the spillover that occurs in n from the tax change in m. In principle, the double difference in outcomes between m and n (which is the total border county effect measure above) and the difference between n and k (the spillover effect) is a measure of the tax effect net of spillovers from, or to, the neighboring county. Of course, there may also be spillovers to and from other states which we will not capture and filter out with this method. Nevertheless, one may think that spillovers to the closest state seem most likely in many cases and could be the largest. The aim of the exercise is to provide an idea of whether spillovers to and from neighboring counties can explain the full magnitude of our results.

The equation estimated is:

$$Y_{mt} - Y_{kt} = \beta_y \Delta T_{it-1}^{yj} + \beta_c \Delta T_{it-1}^c + \gamma \cdot [\mathbb{X}_{mt} - \mathbb{X}_{kt}] + \delta_i + \varepsilon_{it} \tag{8}$$

where i again indexes a pair of border counties in two different states, δ_i is a border pair fixed effect. The left hand-side is the difference in innovation outcomes between the border county m and the average county in the neighboring state (excluding the border county of the pair). ΔT_{it-1}^{yj} is as before the difference in lagged personal tax rates (marginal or average) for income group j, importantly, between the two border counties of the same pair. ΔT_{it-1}^c is as before the difference in lagged corporate tax rates. The set $\mathbb{X}_{it}$ contains again lagged population density, lagged real GDP per capita, and an R&D tax credit measure.

Furthermore, we can combine this estimation strategy with our instrumental variable approach, where, as in Section 6.3, the difference in tax rates ΔT_{it-1}^{yj} and ΔT_{it-1}^c can be instrumented by the difference in instruments, $\Delta \hat{T}_{it-1}^c$ and $\Delta \hat{T}_{it-1}^{yj}$.

The results are shown in Table 9. Overall, the net effects of taxes, even filtering out the spillovers, are still consistently and systematically negatively correlated with patents, citations,

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[14]The IV version of this estimation, not reported, also yields similar coefficients.

inventors, and our other innovation outcome variables. Although spillovers do play a role (since the coefficients are smaller than those not filtering out spillovers), our findings suggest that the the full effect cannot be explained by cross-state business stealing or spillovers, at least when it comes to neighboring counties.

There are also differences in the net effects of the personal and corporate tax rates, relative to their total effects. In relative terms, it appears that the marginal and average taxes at the median, as well as the corporate tax are most prone to spillovers. The effect of the personal tax rate at the 90th percentile is diminished by less after filtering out spillovers.

Finally, to build on this analysis we will also show that at the micro-level the elasticities to taxes are very significant, and that these do not reflect any shifting across states. Combined with the results just presented, we will conclude that cross-state shifting is an important but not complete determinant. In any case, as already mentioned, whether there are spillovers or not, the reduced-form macro estimates are of interest *per se* and reflect the elasticity relevant for a state thinking of unilaterally changing its tax policy.

6.5   Case Studies

We now turn to three special episodes of tax reform in New York, Delaware, and Michigan to provide some sharp visual evidence of the effects of taxes on innovation. Figures 17-18 show the results from each of these episodes. In each case, the black solid line represents the time series in the state under consideration, while the dashed line represents a control state. The control state is constructed according to the synthetic control method of Abadie et al. (2010). That is, it is a weighted average of other states in the sample, where the weights are chosen to best match the average innovation outcome of interest (patents, inventors, or citations), as well as real GDP per capita and population density for the period before the tax change in the state of interest.

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

New York 1968 vs. California

The first case study is shown in Figure 17 and concerns New York's 1968 tax reform bill, in which the top marginal personal income tax rate increased from 10% to 14% and its state top corporate tax rate increased from 5.5% to 7%. The control state here is California, where the top tax rate increased as well from 7% to 10%, but remained lower while the corporate tax rate remained the same at 5.5%. All variables are normalized at their 1965 levels. Before the tax bill, New York and California follow remarkably similar trends for all three innovation outcomes. However, after the

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reform, they diverge and New York performs much worse in terms of innovation relative to the synthetic control.

Michigan 1967-1968

Figure 18 shows the case study of Michigan. Michigan introduced its personal state tax rate in 1967 at 2.6%. One year later, in 1968, it introduced its corporate state tax at 5.6%. The synthetic control for Michigan is composed of several variations on California, Ohio/Pennsylvania, and, for some of the outcome variables, a bit of Texas. While the control state and Michigan evolve very similarly before 1967, Michigan starts performing significantly worse for the innovation outcome measures after the introduction of its tax regime.

Delaware 1969-1970

The third case study concerns Delaware. In 1969, the corporate tax rate increased from 5% to 6%, and in 1970 the personal tax rate increased from 11% to 18%. In this case, the best-fitting synthetic control is comprised of Nevada, California, and Connecticut. Figure 19 shows that the effects on patents, citations, and inventors were noticeably large with the negative trend setting in at the time of the tax reform.

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

7 The Effects of Taxation at the Micro Level: Inventors and Firms

In this Section, we study the effects of taxes at the micro-level of individual firms and inventors.

7.1 Individual Inventor Level

We first describe the general intuition behind this analysis before providing further details and presenting the results. First, at the individual inventor level, our approach to identification comes from using variation in the tax rate across inventors in the same state and same year. This means we include state × year fixed effects, which account for other contemporaneous policy variations and economic circumstances affecting all inventors. To implement this strategy requires assigning inventors to their tax brackets. We do so based on their innovation productivity, which is strongly linked to inventor income. We also include inventor fixed effects. Second, we combine this fixed-effects approach with our instrumental variable strategy, which instruments an inventor's tax with

the predicted tax rate based on federal-level changes, holding state-level taxes fixed.

Constructing Measures of Inventor Productivity

An inventor's productivity at time t could be measured by i) his patent count, i.e., the number of patents produced up to and including time t; ii) his citations-weighted patents (i.e., the total citations an inventor receives); iii) his average citations per patent; or iv) his maximum citations per patent. All these measures capture different dimensions of productivity, respectively, innovation quantity, total patent quality, consistency in the quality, or the maximum quality ever achieved. As our benchmark measure of inventor productivity in year t we use total patents produced until year t. For robustness, we also consider in Appendix Table A7 the citations-weighted patents.

These inventor productivity measures are important independently, but they are also linked to an inventor's income. 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. (2014) match IRS tax data to patent data for U.S. inventors and also highlight the strong link between income and patenting. Using historical data, Akcigit, Grigsby, and Nicholas (2017) establish the link between patents and wages in their match between the 1940 Census and patent data.

Controlling for an Inventor's Tax Rate

Using the productivity measure based on either patents (our benchmark measure) or citations, we can rank inventors nation-wide in each year t. We then call "high-productivity" inventors at time t those inventors who fall in the top 10% of the 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.

We also construct several alternative rankings as robustness checks. First, inventors can be ranked in their state's productivity distribution, rather than the national one. Second, they can be ranked according to a "lifetime" ranking, such that they will be labeled "high-productivity" if they ever fall in the top 10% during their career. This lifetime measure may be the most relevant in a variety of situations. An inventor who has once acquired a good reputation will always tend to generate higher income (e.g. a company will want to retain him). Or if an employer, or the head of an R&D lab, has some advance signal about someone who will invent favorably in the future (before it even shows on the patenting track record) this individual might be paid more *ex ante* in order to attract and retain his talent.

For each possible productivity measure and ranking method, we then assign effective personal income tax rates to each inventor depending on his rank. 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 he is 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 $t - 1$.

Here again, we provide several robustness checks. First, we use alternative cutoffs for which inventors are assigned the 90th percentile personal income tax rate, such as the top 5% or the top 25%. Second, we can assign tax rates to three (or more) rather than just two groups. For instance, the top 10% of the productivity distribution is assumed to face 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 all inventors below the top 25% are assumed to face the tax rate at the median income.

As we will describe below, our results are robust to all of these different variations.

Identification: Fixed effects and Instrumental Variables based on Federal Tax Changes

Our first approach to identification consists of including state × year fixed effects that can absorb other contemporaneous economic developments or policy changes in the state. We also include inventor fixed effects in all regressions. These fixed effects are possible because even within a state and year cell, different inventors face different tax rates due to the fact that they are at different points in the income distribution. Conditional on state × year fixed effects, a spurious correlation between the innovation outcome variables at the individual-level and the effective tax measures could only arise if there are other simultaneous changes that affect differentially high productivity and low productivity inventors and these changes are systematically correlated with the effective tax rates. We also provide a specification with only inventor, state, and year fixed effects, the advantage of which is that we can estimate the effect of corporate tax variation as well (which is otherwise absorbed by the state × year fixed effects).

All regressions also contain the following controls. First, time-varying state-level controls, namely lagged state real GDP per capita and population density. Second, time-varying inventor-level variables, namely the inventor's experience and its square, and the inventor's productivity (which, as just described, can be measured in several different ways). Inventor experience is measured as the number of years since the first patent. We also include an important measure of the agglomeration of innovation in the state, namely the number of patents applied for by other state residents in the inventor's modal technological class in the state in a year $t - 1$ (excluding the inventor's own patents). This agglomeration measure varies by state, inventor, and year, and it captures the fact that different states may be attractive to varying degrees in different years to inventors working in different fields. This could be, for instance, because the state has some specific infrastructure particularly well-suited to innovation in that technology class or because inventors simply like being around others from the same field to interact and learn.

The estimated coefficients on the tax rates can be interpreted as intent-to-treat (ITT) 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 from the outcome directly on the instrument.

In addition to including all the aforementioned fixed effects, we also apply the same IV strategy

as for the macro, state-level regressions above. From our tax calculator, we know the total tax liability (state and federal) of an inventor who is in income group j (where j is either the 90th percentile or the median, according to our ranking of inventor's into tax brackets based on productivity), in state s at time t.[15] In our regressions that only include state and year fixed effects (but not their interaction), we can also instrument for the corporate tax using the previously described predicted tax liability, $\hat{T}_{st}^c$.

7.1.1 Main Results

Our benchmark results are shown in Table 10. The upper panel includes state fixed effects, year fixed effects, and inventor fixed effects (and includes all the state-year varying controls such as GDP per capita or population density). This specification is able to show directly the effect of the corporate tax rate. The lower panel shows the specification with state × year fixed effects and inventor fixed effects, which also absorbs all variation in the corporate tax rate. Reassuringly, the results are extremely similar for the two specifications.

Column 1 studies the likelihood of having a patent over the next three years (between t and $t + 2$, both included). Column 2 shows the likelihood of having successful patents receiving a combined 10 or more citations over the next three years.[16] In the sample, around 41% of patents have 10 citations or more. The extensive margin of patenting is significantly negatively affected by personal income taxes. A one percentage point higher tax rate at the individual level decreases the likelihood of having a patent in the next 3 years by 0.63 percentage points. Similarly, the likelihood of having high quality patents with more than 10 citations decreases by 0.6 percentage points for every percentage point increase in the personal tax rate.

Column 3 shows the effect on the number of log patents, conditional on patenting. Column 4 similarly shows log citations, namely all the citations that accrue to all of the inventor's patents applied for between t and $t + 2$. As explained in our model in Section 5, these reflect intensive margin responses that could be driven by higher effort or more investments. We find that a one percentage point increase in the personal tax rate leads to a 1.1 percent decline in the number of patents and a 1.4-1.7 percent decline in the number of citations, conditional on having any. The implied elasticity of patents is 0.6-0.7, while the implied elasticity of citations is 0.8-0.9. Finally, column 5 shows that the likelihood of having a corporate patent also reacts very negatively to the personal tax rate, and this effect is larger than the effects on patents overall.

In the upper panel, the effects of the corporate tax rate are consistently negative, but they are only significant for the likelihood of having a patent and are generally much smaller in magnitude than the coefficients on the personal income tax variable. Thus, inventors are seemingly more sensitive to personal income tax rates. This makes sense given that they are more directly impacted

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[15]In this IV specification, we can include state × year fixed effects since the instrument varies within state-year cells based on the income group.

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

by the latter, although, as explained in Section 5, inventors could also be influenced by corporate tax rates in a more indirect way through rent-sharing with the firm, or if they plan to incorporate in case of a successful innovation. We thus turn to an analysis that distinguishes between corporate and non corporate inventors.

7.1.2 Corporate Inventors and Agglomeration Forces

In table 11, we study the interaction of the personal tax rate with a dummy for whether the inventor is a corporate inventor. An inventor is defined as a corporate inventor if at least one of his patents over his career is assigned to a company.[17] Corporate inventors are systematically much more sensitive to taxes on personal and corporate income. Recall from the conceptual framework presented in Section 5 that a stronger response to taxes could arise for several reasons: corporate inventors' efforts and investments may simply be more elastic; corporate inventors may place a higher weight on financial returns; corporate inventors' payoffs (i.e., wages) may be highly performance-based, or corporate inventors' inputs may be more complementary to firm inputs R, which are in turn also tax elastic. This finding is consistent with our results at the macro state-level in Section 6, namely that the share of patents assigned is negatively affected by corporate and personal taxes, because corporate patents are more elastic to taxes in general.

The heterogeneous effects of corporate tax in the upper panel are particularly striking. Corporate tax has a strong and significant negative effect on corporate inventors. But it has a mildly positive, although mostly insignificant effect on non-corporate inventors. These diverging results explain why, on average, the effects of the corporate tax in Table 10 were insignificantly negative. The lack of response of non-corporate inventors to corporate taxes accords with the model in Section 5. If self-employed inventors do not select their innovation inputs based on a short-run plan to incorporate or shift profits to the corporate sector immediately (although they may still plan to do this in the future), they should be entirely insensitive to the corporate tax rate. In fact, a mildly positive effect may arise if corporate and non-corporate inventors compete for innovations. Then, a higher corporate tax rate disadvantages the corporate sector relative to the non-corporate sector. Conversely, as shown in the model, corporate inventors are engaged in rent-sharing with firms and are selecting innovation inputs to jointly optimize the surplus from the firm-inventor match. Their payoffs should thus depend at least partially on corporate taxes. The strength of this dependence will be a function of bargaining rules, payoffs, and production technologies. Thus, our finding that corporate inventors are very elastic to corporate taxes, in addition to personal income taxes, is completely in line with the conceptual framework.

Table 12 presents the IV results at the individual inventor level. They are very similar to, but predict somewhat stronger effects than the OLS estimates. There could be two reasons for this.

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[17]Our definition of corporate inventor is destined to flag those inventors who are most likely to fall under the realm of the corporate tax, i.e., those who are either employees, or tightly involved with the corporate sector, e.g., by having a patent done jointly with a company. Corporate inventors are not necessarily employees of companies at all times, although they are very likely to be employees for at least some of the time.

First, there may be measurement error in the OLS estimates given that we need to impute an inventor's tax rate. Even though we do not know whether the measurement error is classical, this could bias the OLS coefficients downwards. Second, state-level taxes could sometimes be set in a counter-cyclical fashion given a state's economic circumstances, which would tend to dampen the negative effect of taxes. Since the IV exploits only federal-level tax changes, it is not correlated with a state's underlying economic conditions. Nevertheless, the upshot is that the magnitudes of the coefficients are very close to those of the OLS estimates, which provides further confidence in the robustness of our results.

Table 14 shows the effects of agglomeration at the micro level. Recall that the agglomeration force is defined as the number of patents applied for by other state residents in the inventor's modal technological class in the state in a given year, divided by 1,000. A consistent finding emerges. Whenever an inventor lives in a state where there is more innovation in his own technological field, he is less sensitive to taxation. To give a sense of the magnitudes, in a state in which there are 1,000 more patents produced in an inventor's technology class, a one percentage point increase in taxes would only lead to a 0.7-0.8 percent decline in patents depending on the specification (respectively, between 0.6 and 0.9 percent decline in citations) instead of a 1.1-1.2 percent decline (respectively, 1.4-1.7 percent decline for citations) in the baseline case.

7.1.3 Robustness Checks

We provide several robustness checks all of which produce substantively similar results.

Our benchmark productivity measure is a dynamic measure that can change over an inventor's life cycle. As a robustness check, in Appendix Table A6, we consider an alternative "lifetime" productivity measure, according to which an inventor is labeled "high-productivity" if he ever falls in the top 10% of the national productivity distribution during his career. In addition, we also consider different cutoffs. Appendix Table A4 shows the results when we define inventors as high productivity if they are in the top 5% of the distribution. In Appendix Table A8, we split inventors into three productivity groups instead: low, medium and high. High productivity inventors are again defined as those in the top 10% of the productivity distribution, medium productivity are those in the top 25% (outside of the top 10) and low productivity are all other inventors. High productivity inventors are assumed to face the tax rate at the 90th percentile of income, medium productivity inventors the marginal tax rate for the 75th percentile, and low productivity inventors are assigned the tax rate applicable at the median income.

Furthermore, because our identification relies on high and low productivity inventors facing different tax rates, we focus in Appendix Table A5 on only "progressive spells," i.e., on periods and states when there was a progressive tax system. Again, our results are similar.

7.2 Location Choice Model

We next estimate a location choice model at the individual inventor-level. Denote by $j[i]$ the tax bracket of inventor i (e.g., 90th income percentile bracket or median income bracket). Suppose that the value to inventor i of living (and inventing) in state s in year t is:

$$U_{ist} = \alpha \log \left(\tau_{st}^{yj[i]} \right) + \beta_s \mathbb{X}_{ist} + \nu_{ist}$$

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 described below, and $\tau_{st}^{yj[i]}$ is the average income tax rate that would apply to inventor i in state s at time t were he to live there. If ν_{ist} is i.i.d with Type 1 extreme value, we can estimate the model using a multinomial logit.

For the sake of computational feasibility and for this estimation only, we restrict ourselves to the fifteen most inventive states, as measured by total patents over the period 1940-2000, and limit our attention to periods when these states have a progressive tax spell. This sample restriction yields possible choice states of California, Maryland, Massachusetts, Minnesota, New Jersey, New York, Ohio, and Wisconsin. We define the home state of an inventor to be the state in which he first patents. 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. "Agglomeration Forces" is again defined to be total patents granted in state s in year t in inventor's i's modal technology class, excluding those granted to inventor i. We also include an interaction of the home state dummy with the high productivity indicator, an interaction of the agglomeration force with the high productivity indicator, as well as a quadratic of the experience of the inventor. The effect of experience is allowed to differ by state, i.e., is interacted with state fixed effects. "Assignee has Patent in Destination" is a dummy equal to one if the employer of the inventor already has had one patent in the state under consideration.

Column 1 of Table 15, which shows the specification with state plus year fixed effects also contains controls for the corporate tax rate, R&D tax credits, real GDP per capita, population density, all lagged by one year. The rest of the columns include state × year fixed effects, making use of the same logic for identification as explained above. Columns 3 to 5 add interactions of the personal average tax rate with additional characteristics of the inventor or the inventor-state pair, namely, an indicator for whether the inventor is a non-corporate inventor, the agglomeration measure, and an indicator variable for whether the assignee that the inventor works for already has a patent in that state.

The main finding from these regressions is that the average tax rate is a strong negative predictor of inventors' location choices. Notice also that it appears particularly important in these estimates to control for state times year fixed effects, since the coefficient in column 2 is much reduced in seize relative to column 1. This suggests that there are other attractive forces or policies in a state that may be correlated with tax rates, and which are filtered out by state × year fixed effects. The effect of taxes in column 2 remains significantly negative and strong even after absorbing state-by-year

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varying factors. The elasticities of the number of inventors residing in a state which are implied by these coefficients can be obtained according to the method in Kleven et al. (2013) and Akcigit et al. (2016). They can be calculated separately for inventors residing in their home state and for inventors residing in another state. With state times year fixed effects, the elasticity to the net-of-tax rate of the number of inventors residing in a state is 0.11 for inventors who are from that state and 1.23 for inventors not from that state.

As expected, there are two strong pull factors – other than taxes – which strongly influence the location decisions of inventors. These are, first, the home state. Inventors are, to a first-order, much more likely to remain in their home state than to move. Second, agglomeration forces are very important as well and increase the appeal of a potential destination state. One can imagine that these agglomeration forces – which are technology field-specific – capture amenities which matter to inventors. They may also be valued *per se* if there are complementarities with other researchers, thanks to interactions or learning (Akcigit et al., 2018).[18] Furthermore, agglomeration influences not only the value an inventor derives from being in a state, but it also dampens the elasticity to taxes, as shown by the interaction term. 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 3 of Table 15 also shows that non-corporate inventors have lower sensitivity to taxes, exactly in line with what we showed in relation to the innovation outcomes above. The same explanations could apply here.

Finally, if an assignee already has a patent in a given state, the inventor is also less sensitive to taxes in that state when making a determination of whether or not to locate there. This could signal either that it is easier to surmount the frictions of moving to another state if one's employer already has a presence there, or that the employer prefers moving inventors to lower tax locations in order to pay them lower compensating differentials as a result – and that this is easy to do when there is already some established presence in that state.

7.3 Individual Firm Level

We now turn to the individual firm-level where the unit of observation is a firm-year. In Table 16, columns 1 through 5 show the coefficients from regressions of the dependent variable in each column on the top corporate tax rate as well as the personal income tax rates at the median and the 90th income percentile. Controls include state fixed effects, for every state in which the firm has a lab, year fixed effects, real GDP per capita, and population density in the state. Panel A shows the OLS results. Panel B shows the IV results, where the total personal and corporate tax liabilities are instrumented with their federal-driven components, as defined in (5) and (6).

The corporate tax rate has a significant effect on the number and log of patents produced

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[18]The agglomeration measure can also capture congestion effects, which we would expect to play a negative role. Thus, the coefficient should be interpreted as a net effect of agglomeration, which appears positive. In addition, the state × year fixed effects would capture general price or wage effects arising from higher or lower skill supply.

by the firm each year, the number and log of citations, and the number of research workers. A one percentage point decrease in the corporate tax rate increases patents by 4% and citations by around 3.5%. The IV results are of similar magnitudes, but again even stronger. According to the IV specification, a one percentage point decrease in the corporate tax rate increases patents by 6% and citations by 5%.

The personal income tax rate also influences firm-level innovation outcomes, but in an interesting non-linear way, and less strongly so than does the corporate tax variable. The marginal tax rate at the median income level is negatively related to innovation outcomes at the firm level, and the magnitudes of the coefficients are smaller and less significant than the estimated coefficients with respect to the corporate tax rate. However, the marginal tax rate at the 90th percentile of income has insignificant effects and the coefficients are sometimes positive but also insignificant. This pattern in the coefficients makes sense if the bulk of firms' employees are not in the top 10% tax bracket, so the marginal tax rate of the median earner is the main driver. Note that this pattern is different for the number of research workers employed where the effect of personal income tax at the median income level on the number of research workers is as strong as the effect of the corporate tax. Personal taxes would be expected to be an important determinant of research workers employed in R&D labs if firms are moderating the impact of at least part of its incidence.

Finally, Panel A, column 6 estimates a location choice model for new lab openings, in the spirit of the multinomial logit of inventor location from Section 7.2. This specification allows us to examine, conditional on opening a new lab, where the firm decides to locate it. We restrict the choice set to the 15 top innovative states, as ranked by total patents between 1920 and 2000, due to computational feasibility. The top corporate tax rate has a significantly negative effect on the decision of a firm to locate its lab in a given state. This finding supports the results from Section 7.1 at the individual inventor level. Overall, taxes seem to be an important predictor of the location of innovation.

8   Conclusion

We have studied the effects of personal and corporate income taxes on innovation in the United States during the 20th century using a series of newly constructed datasets. Our data is sufficiently wide-ranging that we can consider both inventors and firms engaged in inventive activity over a long time period, and we can exploit the numerous changes to the U.S. tax code taking place over the 20th century. We document the effect of taxes at the macro (state) and micro (inventors and firm) levels and attempt to identify the estimates empirically. We find that both personal and corporate taxes matter for innovation. The quantity, quality, and the location of innovation are all affected by the tax system and the effects are quantitatively important.

In addition to being able to document and identify these important responses to taxation, our estimates can help calibrate the tax elasticities needed in optimal tax formulas for labor or capital income (see Saez (2001) and Saez and Stantcheva (2018)), as well as quantify the efficiency costs

of taxation, which are traded off against the revenue gains. Furthermore, our empirical evidence provides a sense of how firms and inventors respond to the net return to innovation, and not only to tax rates, which are merely a component of that economic calculation.

In future work, it would be fruitful to compare the U.S. experience to other countries, historically and contemporaneously. That would require a major data collection effort, as we have undertaken for the U.S., but our analysis highlights the benefits of such investments. Currently we know very little about the impact of taxation on innovation over long time horizons, and our analysis is therefore an important first-step in building a better understanding of a relationship that is critical in policy discussions. While our estimates show that the state-level effects of taxes are not purely due to zero-sum business-stealing, it is still an open question as to how the federal tax rate affects national-level innovation in the U.S., when taking into account the international mobility of inventors, firms and intellectual property. An answer to that question is central to a fuller understanding of a tax regime's real impact.

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Table 1: Disambiguation Performance

Sample	# Inventors	# Patents
1920-2004, All Countries	4,890,574	6,443,227
1920-2004, US only	2,734,229	4,208,876
1940-2000, US only	1,953,066	2,775,209
Lai et al. Patents, New Disambig.	3,342,989	3,984,771
Lai et al. Disambiguation	2,998,661	3,984,771
Lai et al. US Patents, New Disambig.	1,572,011	2,179,741
Lai et al. Disambig (US)	1,462,207	2,179,741

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

Table 2: Summary Statistics on Inventor Careers

	Mean	SD	90th	95th	99th
Years Active	3.08	6.10	7.00	14.00	31.00
Number of States	1.06	0.35	1.00	1.00	3.00
Number of Patents	2.55	6.47	5.00	8.00	26.00
Patents Per Year	1.02	0.48	1.00	2.00	3.00
Total Citations Received	83.42	736.46	119.03	265.18	1189.25
Citations Per Year	27.12	133.45	48.38	91.93	329.10
Number of Classes	1.83	2.84	3.00	5.00	14.00

Notes: Table reports summary statistics of our sample of disambiguated inventors. The categories "Number of States," "Number of Patents," "Total Citations Received," and "Number of Classes" refer to statistics over an inventor's entire career, while "Patents Per Year" and "Citations Per Year" refer to average numbers per year of an inventor's career.

	Log Patents	Log Citations	Log Inventors	Log Superstars	Citations/ Patent	Share Assigned
	(1)	(2)	(3)	(4)	(5)	(6)
90th Pctile Income MTR	-0.041***	-0.040***	-0.040***	-0.047***	-0.085*	-0.334***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.044)	(0.077)
Top Corporate MTR	-0.063***	-0.059***	-0.051***	-0.093***	0.039	-1.090***
	(0.007)	(0.008)	(0.006)	(0.011)	(0.068)	(0.159)
Median Income MTR	-0.045***	-0.046***	-0.046***	-0.060***	0.033	-0.065
	(0.005)	(0.005)	(0.004)	(0.006)	(0.051)	(0.087)
Top Corporate MTR	-0.064***	-0.059***	-0.051***	-0.091***	-0.002	-1.189***
	(0.008)	(0.009)	(0.007)	(0.012)	(0.063)	(0.173)
90th Pctile Income ATR	-0.063***	-0.060***	-0.062***	-0.081***	0.080	-0.135
	(0.004)	(0.005)	(0.004)	(0.007)	(0.054)	(0.100)
Top Corporate MTR	-0.058***	-0.055***	-0.046***	-0.085***	-0.017	-1.167***
	(0.007)	(0.008)	(0.007)	(0.011)	(0.062)	(0.173)
Median Income ATR	-0.100***	-0.108***	-0.091***	-0.150***	-0.621***	-0.672***
	(0.008)	(0.011)	(0.007)	(0.010)	(0.144)	(0.146)
Top Corporate MTR	-0.061***	-0.055***	-0.050***	-0.085***	0.113	-1.096***
	(0.007)	(0.008)	(0.007)	(0.011)	(0.075)	(0.161)
Observations	2867	2867	2867	2661	2867	2867
Mean of Dep. Var.	7.18	9.87	7.31	4.37	17.68	71.74
S.D. of Dep. Var.	1.31	1.59	1.33	1.60	12.48	14.01

Notes: White heteroskedasticity robust standard errors clustered at year level reported in parentheses. Regressions follow the format described in (4). All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state and year fixed effects. Tax rates measured in percentage points and lagged by 1 year. Regressions weighted by state-year level population counts.

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Log Superstars (4)	Citations/ Patent (5)	Share Assigned (6)
90th Pctile Income MTR	-0.048***	-0.046***	-0.046***	-0.055***	-0.082	-0.349***
	(0.006)	(0.007)	(0.005)	(0.008)	(0.059)	(0.086)
Top Corporate MTR	-0.068***	-0.059***	-0.056***	-0.105***	0.255***	-1.008***
	(0.008)	(0.010)	(0.007)	(0.011)	(0.087)	(0.188)
Median Income MTR	-0.032***	-0.029***	-0.034***	-0.041***	0.244***	0.252***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.095)	(0.088)
Top Corporate MTR	-0.074***	-0.066***	-0.059***	-0.110***	0.115	-1.261***
	(0.009)	(0.010)	(0.008)	(0.012)	(0.077)	(0.194)
90th Pctile Income ATR	-0.060***	-0.057***	-0.060***	-0.075***	0.095	0.038
	(0.006)	(0.008)	(0.005)	(0.009)	(0.088)	(0.120)
Top Corporate MTR	-0.063***	-0.055***	-0.050***	-0.098***	0.183**	-1.166***
	(0.008)	(0.010)	(0.007)	(0.012)	(0.077)	(0.196)
Median Income ATR	-0.101***	-0.108***	-0.091***	-0.148***	-0.589***	-0.370**
	(0.012)	(0.016)	(0.010)	(0.016)	(0.190)	(0.180)
Top Corporate MTR	-0.066***	-0.055***	-0.055***	-0.097***	0.346***	-1.073***
	(0.009)	(0.010)	(0.007)	(0.012)	(0.093)	(0.184)
Observations	2867	2867	2867	2661	2867	2867
Mean of Dep. Var.	7.18	9.87	7.31	4.37	17.68	71.74
S.D. of Dep. Var.	1.31	1.59	1.33	1.60	12.48	14.01

Notes: The period covered is 1940-2000. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state-specific linear trends and state fixed effects. Tax rates measured in percentage points and lagged by 1 year.

TABLE 5: BORDER COUNTY ESTIMATIONS: TOTAL EFFECTS (OLS)

Dependent Variable:	Log Patents	Log Citations	Log Inventors	Citations/ Patent	Log Corp. Patents
	(1)	(2)	(3)	(4)	(5)
90th Pctile Personal Income MTR (%, lag)	-0.020***	-0.021***	-0.021***	0.018	-0.021***
	(0.004)	(0.006)	(0.004)	(0.107)	(0.005)
Top Corporate MTR (%, lag)	-0.028***	-0.054***	-0.022**	-0.641***	-0.023**
	(0.009)	(0.012)	(0.010)	(0.176)	(0.010)
Median Personal Income MTR (%, lag)	-0.068***	-0.073***	-0.054***	-0.197	-0.060***
	(0.006)	(0.009)	(0.006)	(0.140)	(0.007)
Top Corporate MTR (%, lag)	-0.028***	-0.054***	-0.023**	-0.621***	-0.024**
	(0.009)	(0.013)	(0.011)	(0.174)	(0.011)
90th Pctile Personal Income ATR (%, lag)	-0.078***	-0.086***	-0.067***	-0.247	-0.072***
	(0.007)	(0.010)	(0.007)	(0.177)	(0.008)
Top Corporate MTR (%, lag)	-0.023**	-0.049***	-0.019*	-0.604***	-0.020*
	(0.009)	(0.012)	(0.010)	(0.169)	(0.011)
Median Personal Income ATR (%, lag)	-0.105***	-0.122***	-0.103***	-0.455***	-0.098***
	(0.014)	(0.016)	(0.015)	(0.158)	(0.016)
Top Corporate MTR (%, lag)	-0.035***	-0.062***	-0.029**	-0.643***	-0.031**
	(0.011)	(0.014)	(0.012)	(0.177)	(0.012)
Observations	8314	8314	8314	8314	8239
Mean of Dep. Var.	0.030	0.033	0.040	-0.135	0.042
S.D. of Dep. Var.	1.460	1.658	1.497	14.411	1.581

Notes: Table reports estimates from equation 7. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as county pair fixed effects. Tax rates measured in percentage points and lagged by 1 year. Only county pairs where both counties have at least 6 patents in year t are included.

TABLE 6: BORDER COUNTY ESTIMATIONS: TOTAL EFFECTS (IV)

Dependent Variable:	Log Patents	Log Citations	Log Inventors	Citations/ Patent	Log Corp. Patents
	(1)	(2)	(3)	(4)	(5)
90th Pctile Personal Income MTR (%, lag)	-0.023***	-0.025***	-0.020***	-0.125	-0.021***
	(0.005)	(0.006)	(0.005)	(0.103)	(0.006)
Top Corporate MTR (%, lag)	-0.066***	-0.111***	-0.051***	-1.195***	-0.066***
	(0.015)	(0.022)	(0.018)	(0.387)	(0.017)
Median Personal Income MTR (%, lag)	-0.075***	-0.080***	-0.048***	-0.561**	-0.063***
	(0.007)	(0.011)	(0.008)	(0.221)	(0.008)
Top Corporate MTR (%, lag)	-0.047***	-0.091***	-0.040**	-1.035***	-0.051***
	(0.017)	(0.022)	(0.020)	(0.348)	(0.019)
90th Pctile Personal Income ATR (%, lag)	-0.089***	-0.099***	-0.063***	-0.690***	-0.076***
	(0.008)	(0.010)	(0.009)	(0.253)	(0.010)
Top Corporate MTR (%, lag)	-0.045***	-0.088***	-0.038*	-1.016***	-0.049***
	(0.016)	(0.021)	(0.020)	(0.351)	(0.018)
Median Personal Income ATR (%, lag)	-0.163***	-0.185***	-0.135***	-1.252***	-0.144***
	(0.019)	(0.025)	(0.018)	(0.365)	(0.021)
Top Corporate MTR (%, lag)	-0.065***	-0.109***	-0.050**	-1.166***	-0.065***
	(0.020)	(0.026)	(0.023)	(0.378)	(0.021)
Observations	8314	8314	8314	8314	8239
Mean of Dep. Var.	0.030	0.033	0.040	-0.135	0.042
S.D. of Dep. Var.	1.460	1.658	1.497	14.411	1.581

Notes: Table reports estimates from equation 7. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as county pair fixed effects. Tax rates measured in percentage points and lagged by 1 year. Only county pairs where both counties have at least 6 patents in year t are included.

TABLE 7: MACRO EFFECTS OF TAXES: EXCLUDING MOVERS (IV)

	Log Patents (1)	Log Citations (2)	Log Inventor (3)	Citations/ Patent (4)	Share Assigned (5)
90th Pctile Income MTR	-0.048***	-0.048***	-0.046***	-0.081	-0.427***
	(0.005)	(0.007)	(0.005)	(0.057)	(0.083)
Top Corporate MTR	-0.068***	-0.068***	-0.055***	-0.052	-1.055***
	(0.008)	(0.009)	(0.007)	(0.069)	(0.182)
Median Income MTR	-0.033***	-0.025***	-0.034***	0.332***	0.169*
	(0.003)	(0.005)	(0.003)	(0.109)	(0.087)
Top Corporate MTR	-0.073***	-0.076***	-0.059***	-0.230**	-1.304***
	(0.009)	(0.010)	(0.007)	(0.093)	(0.186)
90th Pctile Income ATR	-0.062***	-0.055***	-0.060***	0.185**	-0.088
	(0.006)	(0.008)	(0.005)	(0.088)	(0.118)
Top Corporate MTR	-0.063***	-0.065***	-0.050***	-0.159**	-1.195***
	(0.008)	(0.009)	(0.007)	(0.077)	(0.188)
Median Income ATR	-0.096***	-0.102***	-0.088***	-0.474***	-0.525***
	(0.011)	(0.014)	(0.010)	(0.141)	(0.176)
Top Corporate MTR	-0.067***	-0.066***	-0.055***	0.015	-1.119***
	(0.008)	(0.010)	(0.007)	(0.064)	(0.176)
Observations	2867	2867	2867	2867	2867
Mean of Dep. Var.	6.90	9.56	7.11	16.85	68.40
S.D. of Dep. Var.	1.30	1.57	1.32	11.31	14.66

Notes: White heteroskedasticity robust standard errors clustered at year level reported in parentheses. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state and year fixed effects. Tax rates measured in percentage points and lagged by 1 year. Regressions weighted by state-year level population counts.

TABLE 8: BORDER COUNTY ESTIMATES: EXCLUDING MOVERS

Dependent Variable:	Log Patents	Log Citations	Log Inventors	Citations/ Patent	Log Corp. Patents
	(1)	(2)	(3)	(4)	(5)
90th Pctile Personal Income MTR (%, lag)	-0.017***	-0.013*	-0.016***	0.076	-0.015***
	(0.004)	(0.007)	(0.005)	(0.107)	(0.005)
Top Corporate MTR (%, lag)	-0.009	-0.030**	-0.007	-0.605**	-0.001
	(0.009)	(0.014)	(0.010)	(0.250)	(0.010)
Median Personal Income MTR (%, lag)	-0.064***	-0.065***	-0.051***	-0.198	-0.059***
	(0.007)	(0.011)	(0.007)	(0.186)	(0.008)
Top Corporate MTR (%, lag)	-0.008	-0.029**	-0.007	-0.568**	-0.000
	(0.010)	(0.014)	(0.011)	(0.233)	(0.012)
90th Pctile Personal Income ATR (%, lag)	-0.073***	-0.070***	-0.061***	-0.176	-0.069***
	(0.007)	(0.010)	(0.007)	(0.172)	(0.008)
Top Corporate MTR (%, lag)	-0.004	-0.025*	-0.003	-0.561**	0.004
	(0.010)	(0.013)	(0.010)	(0.232)	(0.011)
Median Personal Income ATR (%, lag)	-0.107***	-0.123***	-0.106***	-0.421**	-0.111***
	(0.015)	(0.020)	(0.015)	(0.197)	(0.017)
Top Corporate MTR (%, lag)	-0.015	-0.036**	-0.013	-0.591**	-0.007
	(0.011)	(0.015)	(0.012)	(0.243)	(0.013)
Observations	8302	8295	8307	8302	8131
Mean of Dep. Var.	0.050	0.052	0.060	-0.235	0.078
S.D. of Dep. Var.	1.527	1.774	1.558	15.055	1.666

Notes: OLS results. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as county pair fixed effects. Tax rates measured in percentage points and lagged by 1 year. Only county pairs where both counties have at least 6 patents in year t are included.

TABLE 9: BORDER COUNTY ESTIMATIONS: NET EFFECTS

Dependent Variable:	Log Patents	Log Citations	Log Inventors	Citations/ Patent	Log Corp. Patents
	(1)	(2)	(3)	(4)	(5)
90th Pctile Personal Income MTR (%, lag)	-0.018***	-0.009*	-0.018***	0.193**	-0.020***
	(0.003)	(0.005)	(0.003)	(0.075)	(0.004)
Top Corporate MTR (%, lag)	-0.016**	-0.025**	-0.008	-0.372**	-0.022**
	(0.008)	(0.011)	(0.008)	(0.153)	(0.010)
Median Personal Income MTR (%, lag)	-0.029***	-0.022***	-0.023***	0.151	-0.019***
	(0.006)	(0.008)	(0.006)	(0.096)	(0.007)
Top Corporate MTR (%, lag)	-0.019**	-0.026**	-0.011	-0.330**	-0.027**
	(0.008)	(0.011)	(0.009)	(0.148)	(0.010)
90th Pctile Personal Income ATR (%, lag)	-0.038***	-0.021**	-0.032***	0.408***	-0.031***
	(0.006)	(0.009)	(0.006)	(0.117)	(0.008)
Top Corporate MTR (%, lag)	-0.016*	-0.025**	-0.008	-0.372**	-0.024**
	(0.008)	(0.011)	(0.008)	(0.151)	(0.010)
Median Personal Income ATR (%, lag)	-0.017*	0.002	-0.019**	0.643***	-0.002
	(0.009)	(0.012)	(0.009)	(0.187)	(0.011)
Top Corporate MTR (%, lag)	-0.022**	-0.028**	-0.013	-0.302*	-0.028***
	(0.009)	(0.011)	(0.009)	(0.152)	(0.010)
Observations	8809	8808	8809	8809	8725
Mean of Dep. Var.	0.059	-0.020	0.030	-0.887	-0.012
S.D. of Dep. Var.	1.556	1.830	1.574	13.281	1.641

Notes: OLS Results. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as county pair fixed effects. Tax rates measured in percentage points and lagged by 1 year. Only county pairs where both counties have at least 6 patents in year t are included.

TABLE 10: EFFECTS OF TAXES AT THE INDIVIDUAL INVENTOR LEVEL (OLS)

Dependent Variable:	Has Patent (3-year) (1)	Has 10+ Cites (3-year) (2)	Log Patents (3-year) (3)	Log Citations (3-year) (4)	Has Corporate Patent (3-yr) (5)
Effective MTR	-0.629***	-0.602***	-0.012***	-0.016***	-0.667***
	(0.101)	(0.109)	(0.003)	(0.003)	(0.082)
Top Corporate MTR	-0.201*	-0.100	-0.002	-0.001	-0.091
	(0.104)	(0.102)	(0.002)	(0.003)	(0.093)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.626***	-0.569***	-0.011***	-0.013***	-0.642***
	(0.103)	(0.109)	(0.003)	(0.003)	(0.084)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5956315	5956315	4545384	4392312	5956315
Mean of Dep. Var.	76.312	45.079	0.442	2.758	61.421
S.D. of Dep. Var.	42.517	49.757	0.664	1.453	48.678

Notes: Standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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.

TABLE 11: EFFECTS OF TAXES ON CORPORATE VS. NON CORPORATE INVENTORS

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)
	(1)	(2)	(3)	(4)
Effective MTR	-0.075	-0.535***	-0.014***	-0.026***
	(0.203)	(0.165)	(0.003)	(0.005)
MTR × Corp. Inv.	-0.605***	-0.094	0.002	0.009***
	(0.175)	(0.114)	(0.002)	(0.003)
Top Corporate MTR	0.044	0.238	0.005*	0.013**
	(0.177)	(0.143)	(0.003)	(0.005)
Corp. MTR × Corp. Inv.	-0.201	-0.348***	-0.007***	-0.015***
	(0.173)	(0.105)	(0.002)	(0.004)
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y
Effective MTR	0.053	-0.298**	-0.009***	-0.015***
	(0.156)	(0.135)	(0.003)	(0.003)
MTR × Corp. Inv.	-0.708***	-0.285***	-0.002**	0.002
	(0.106)	(0.046)	(0.001)	(0.001)
State × Year FE	Y	Y	Y	Y
Observations	5956315	5956315	4545384	4392312
Mean of Dep. Var.	76.312	45.079	0.442	2.758
S.D. of Dep. Var.	42.517	49.757	0.664	1.453

Notes: Standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Corporate inventors defined as those who ever have a patent assigned to a corporation. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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.

TABLE 12: EFFECTS OF TAXES AT THE INDIVIDUAL INVENTOR LEVEL (IV)

Dependent Variable:	Has Patent (3-year) (1)	Has 10+ Cites (3-year) (2)	Log Patents (3-year) (3)	Log Citations (3-year) (4)	Has Corporate Patent (3-yr) (5)
Effective MTR	-0.647***	-0.622***	-0.013***	-0.017***	-0.695***
	(0.025)	(0.026)	(0.000)	(0.001)	(0.025)
Top Corporate MTR	-0.172**	-0.063	0.000	0.004*	0.047
	(0.072)	(0.071)	(0.001)	(0.002)	(0.070)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.119***	-0.184***	-0.005***	-0.006***	-0.136***
	(0.025)	(0.029)	(0.001)	(0.001)	(0.021)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5956315	5956315	4545384	4392312	5956315
Mean of Dep. Var.	76.312	45.079	0.442	2.758	61.421
S.D. of Dep. Var.	42.517	49.757	0.664	1.453	48.678

Notes: Standard errors clustered at the state-year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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.

TABLE 13: EFFECTS OF TAXES ON CORPORATE VS. NON CORPORATE INVENTORS (IV)

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)
	(1)	(2)	(3)	(4)
Effective MTR	-0.083**	-0.550***	-0.014***	-0.026***
	(0.037)	(0.035)	(0.001)	(0.001)
MTR × Corp. Inv.	-0.610***	-0.092***	0.002***	0.009***
	(0.029)	(0.025)	(0.000)	(0.001)
Top Corporate MTR	-0.057	0.240**	0.007***	0.020***
	(0.116)	(0.114)	(0.002)	(0.004)
Corp. MTR × Corp. Inv.	-0.200***	-0.354***	-0.007***	-0.015***
	(0.024)	(0.021)	(0.000)	(0.001)
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y
Effective MTR	0.166***	-0.048	-0.004***	-0.004***
	(0.044)	(0.038)	(0.001)	(0.001)
MTR × Corp. Inv.	-0.286***	-0.131***	-0.002***	-0.002**
	(0.039)	(0.028)	(0.001)	(0.001)
State × Year FE	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y
Observations	5956315	5956315	4545384	4392312
Mean of Dep. Var.	76.312	45.079	0.442	2.758
S.D. of Dep. Var.	42.517	49.757	0.664	1.453

Notes: White heteroskedasticity robust standard errors reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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.

TABLE 14: THE MICRO EFFECTS OF AGGLOMERATION

Dependent Variable:	Has Patent (3-year) (1)	Has 10+ Cites (3-year) (2)	Log Patents (3-year) (3)	Log Citations (3-year) (4)	Has Corporate Patent (3-yr) (5)
Effective MTR	-0.635***	-0.620***	-0.012***	-0.017***	-0.669***
	(0.102)	(0.109)	(0.003)	(0.003)	(0.083)
Effective MTR × Agglom.	0.082	0.277***	0.004*	0.006*	0.022
	(0.061)	(0.080)	(0.002)	(0.003)	(0.057)
Top Corporate MTR	-0.200*	-0.098	-0.002	-0.001	-0.091
	(0.104)	(0.102)	(0.002)	(0.003)	(0.093)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.634***	-0.591***	-0.011***	-0.014***	-0.646***
	(0.104)	(0.109)	(0.003)	(0.003)	(0.084)
Effective MTR × Agglom.	0.114*	0.325***	0.004*	0.008**	0.058
	(0.064)	(0.085)	(0.002)	(0.003)	(0.057)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5960366	5960366	4548116	4394959	5960366
Mean of Dep. Var.	76.306	45.078	0.442	2.758	61.408
S.D. of Dep. Var.	42.521	49.757	0.664	1.454	48.681

Notes: White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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 in the state.

TABLE 15: MULTINOMIAL LOGISTIC REGRESSION ESTIMATES

	(1)	(2)	(3)	(4)	(5)
Effective ATR	-0.093***	-0.025**	-0.026**	-0.026**	-0.121***
	(0.009)	(0.012)	(0.012)	(0.012)	(0.013)
Agglomeration Forces	1.217***	1.216***	1.216***	0.994***	1.112***
	(0.029)	(0.030)	(0.030)	(0.072)	(0.030)
Home State Flag	3.866***	3.868***	3.869***	3.868***	3.690***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Interaction coefficients:					
Non-Corporate Inventor			0.071***		
			(0.017)		
Agglomeration				0.016***	
				(0.004)	
Assignee Has Patent					0.130***
					(0.001)
Fixed Effects	State + Year	State × Year	State × Year	State × Year	State × Year
Observations	1951513	1951513	1951513	1951513	1951513

Notes: Table reports coefficients estimated from the multinomial logistic regression specified in Section 7.2. 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. White heteroskedasticity robust standard errors clustered at inventor level reported in parentheses. All tax rates on percentage point scale, and lagged by one year. Includes home state × high productivity FEs. For the sake of computational feasibility, we restrict ourselves to the fifteen most inventive states, as measured by total patents over the period 1940-2000, and limit our attention to periods when these states have a progressive tax spell. This sample restriction yields possible choice states of California, Maryland, Massachusetts, Minnesota, New Jersey, New York, Ohio, and Wisconsin.

TABLE 16: REGRESSIONS AT THE FIRM LEVEL

	Panel A: OLS					
Dependent Variable:	# of Patents	Log Patents	# of Citations	Log Citations	# of Research Workers	Location Choice
	(1)	(2)	(3)	(4)	(5)	(6)
Top Corporate MTR	-0.392**	-0.042***	-23.524***	-0.039***	-9.829	-0.026**
	(0.171)	(0.012)	(4.282)	(0.015)	(7.948)	(0.013)
90th Percentile MTR	0.076	0.018	-1.318	0.013	-9.655**	-0.049***
	(0.105)	(0.011)	(3.691)	(0.014)	(3.826)	(0.015)
50th Percentile MTR	-0.331**	-0.028	-9.097*	-0.025	-9.749	-0.072***
	(0.162)	(0.018)	(5.310)	(0.022)	(7.062)	(0.035)
Observations	147777	34572	147777	33679	28918	11901

	Panel B: Instrumental Variables					
Top Corporate MTR	-0.639**	-0.059***	-31.352***	-0.053**	-42.246**	
	(0.299)	(0.017)	(6.325)	(0.021)	(18.718)	
90th Percentile MTR	0.089	0.024*	2.059	0.021	-5.977*	
	(0.118)	(0.013)	(4.035)	(0.016)	(3.506)	
50th Percentile MTR	-0.375	-0.025	-16.512***	-0.022	-40.111**	
	(0.229)	(0.022)	(6.384)	(0.028)	(16.158)	
State FE	Y	Y	Y	Y	Y	
Year FE	Y	Y	Y	Y	Y	
Observations	147777	34572	147777	33679	28918	
Mean of Dep. Var.	2.924	1.310	103.764	3.253	71.162	
S.D. of Dep. Var.	21.872	1.300	365.764	1.591	643.434	

Notes: Columns 1 through 4 present estimates from linear regressions at the firm level. Column 5 reports estimated coefficients from a multinomial logistic regression on location choice for new lab entry. For computational simplicity, we allow firms to locate their labs in one of the top 15 states, ranked by total patents between 1920 and 2000. Tax rates measured in percentage points and lagged by one year. In Panel B, personal tax rates and corporate tax rates are instrumented for by the predicted tax rates given by (5) and (6) respectively. All regressions include controls for average GDP per capita and population density in the states in which the firm operates labs, weighted by the number of labs in each state. For the linear regressions, state fixed effects refer to a set of dummy variables equal to 1 if the firm has at least one R&D lab in the state. For column 6, state fixed effects control for the baseline probability that a firm locates a lab in state s. Number of observations in column 6 refers to the number of new lab openings in our data. White heteroskedasticity robust standard errors reported in parentheses. Multinomial logistic regression only includes state tax rates, rather than combined federal and state tax rates, in the explanatory variable set. Location choice also contains state-specific trends as a control.
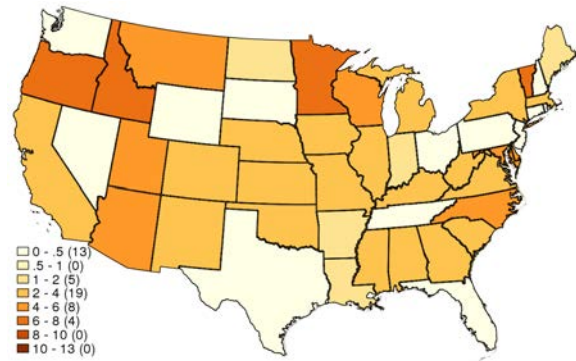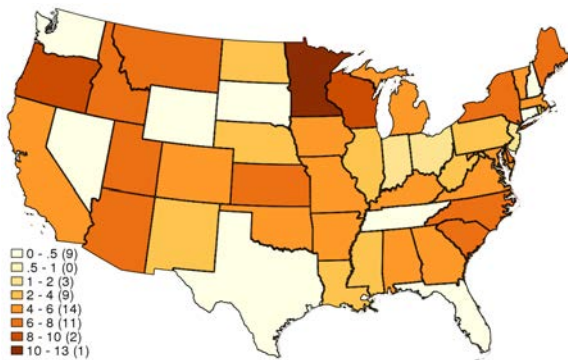
FIGURE 3: PATENTS PER CAPITA OVER TIME
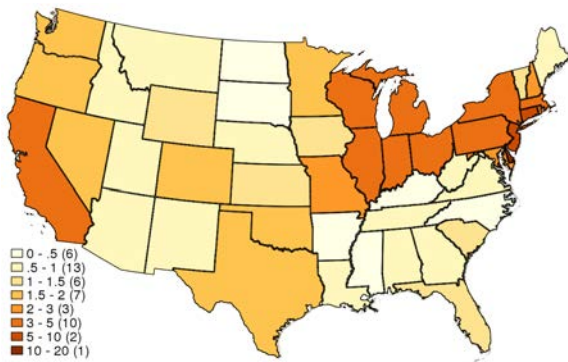
PANEL A: 1940
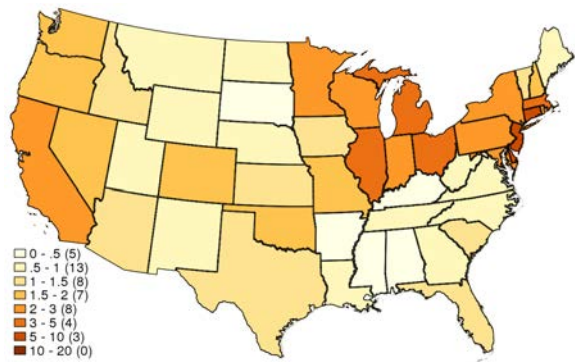
PANEL B: 1950
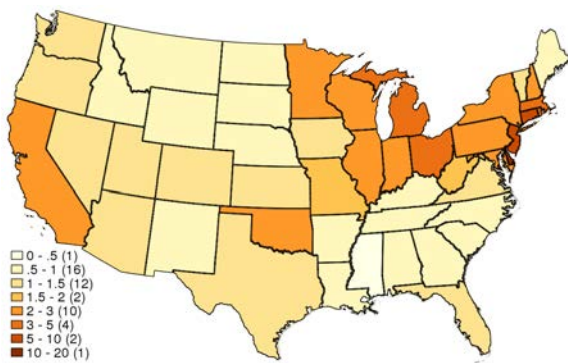
PANEL C: 1960
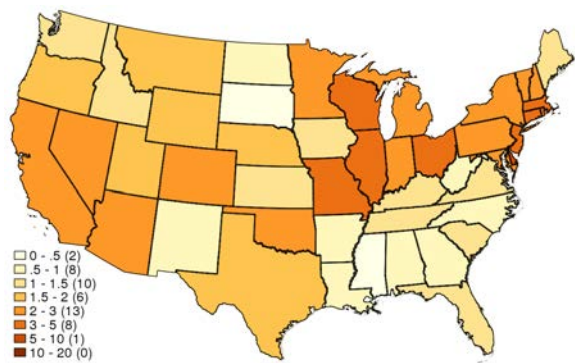
PANEL D: 1970
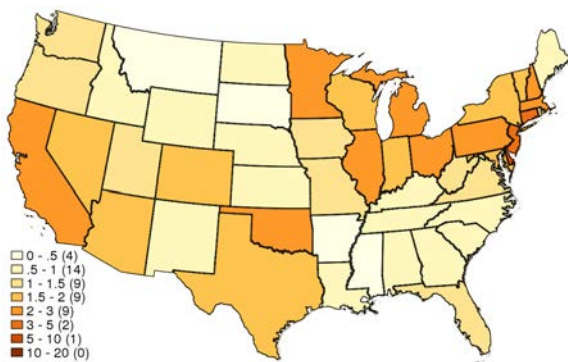
PANEL E: 1980
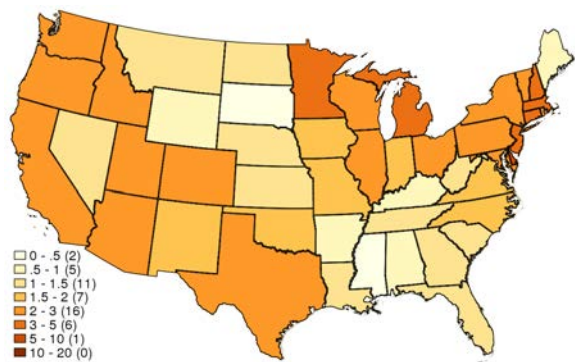
PANEL F: 1990
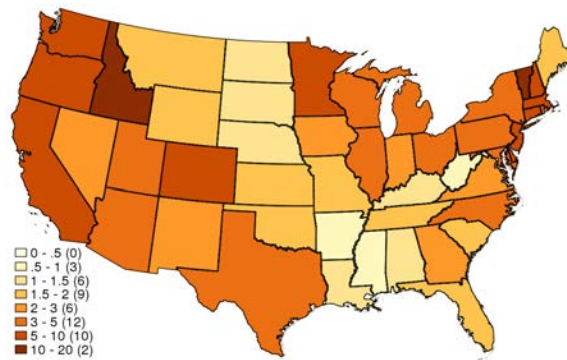
PANEL G: 2000

FIGURE 4: SHARE OF CORPORATE PATENTS AND CORPORATE INVENTORS
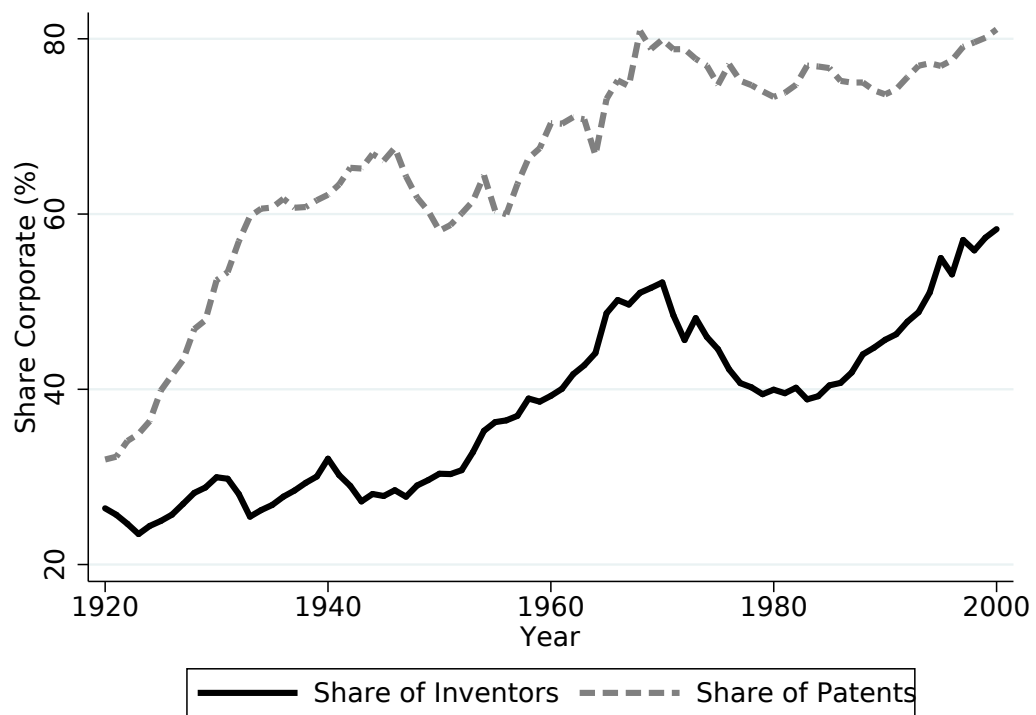
Notes: The graph shows the share of patents assigned to corporations (dashed line) and the share of inventors who patent for corporations (solid line).

FIGURE 5: LOCATIONS OF FIRM R&D LABS

PANEL A: 1921
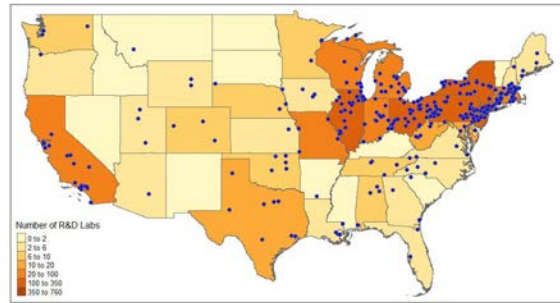
PANEL B: 1927
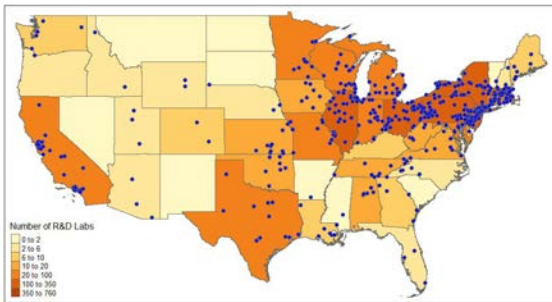
PANEL C: 1933
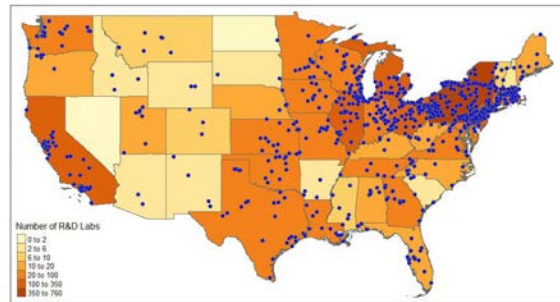
PANEL D: 1940
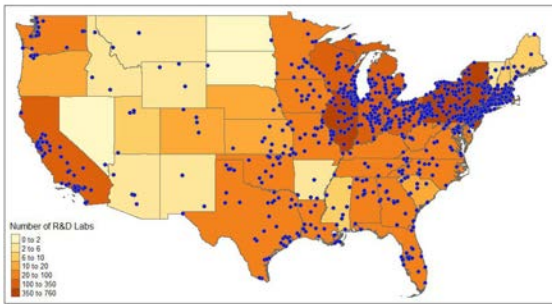
PANEL E: 1950
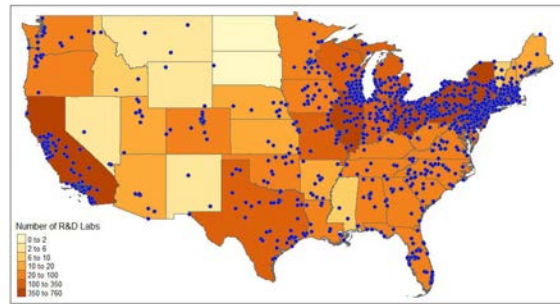
PANEL F: 1960
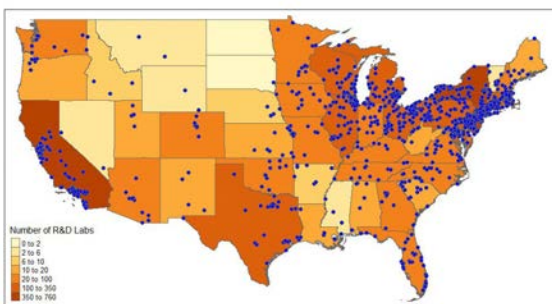
PANEL E: 1965
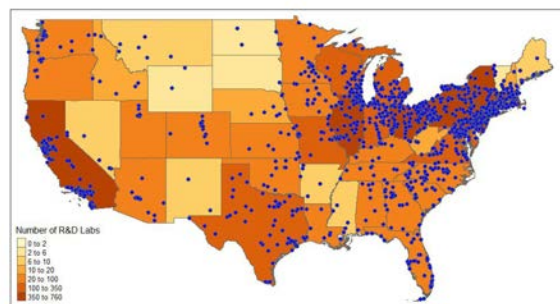
PANEL F: 1970

Notes: Map plots locations of firm R&D labs for a sample of eight National Research Council Surveys of Industrial
Research Laboratories of the United States (IRLUS) directory years.
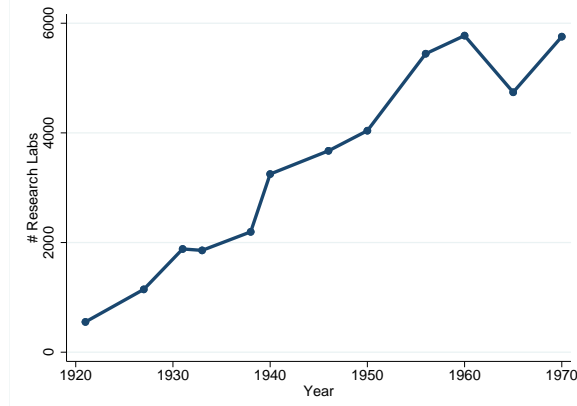
PANEL A: TOTAL NUMBER OF LABS
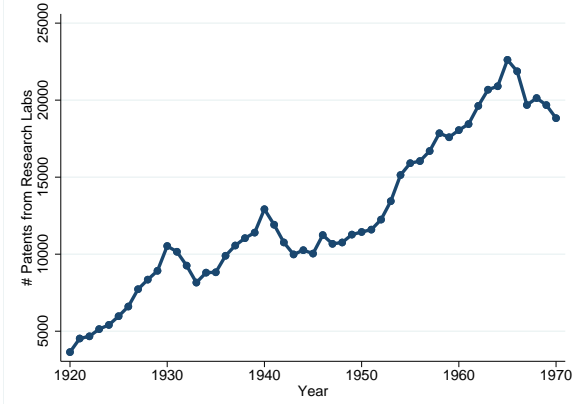
PANEL B: TOTAL PATENTS FROM LABS
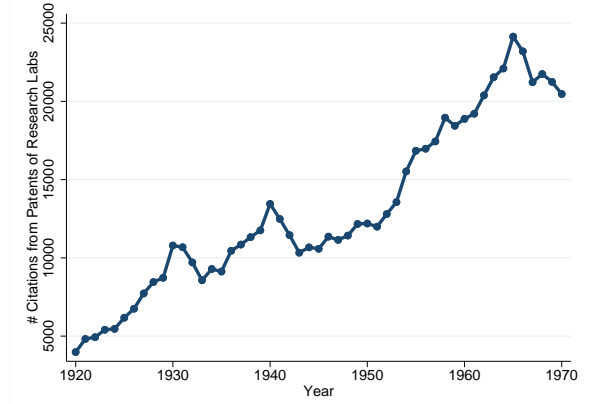
PANEL C: CITATIONS RECEIVED BY LABS
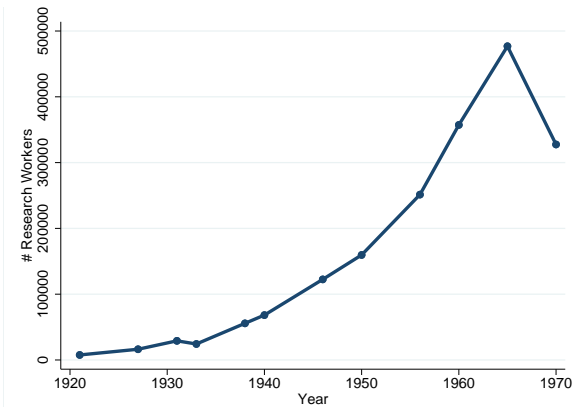
PANEL D: TOTAL RESEARCH WORKERS
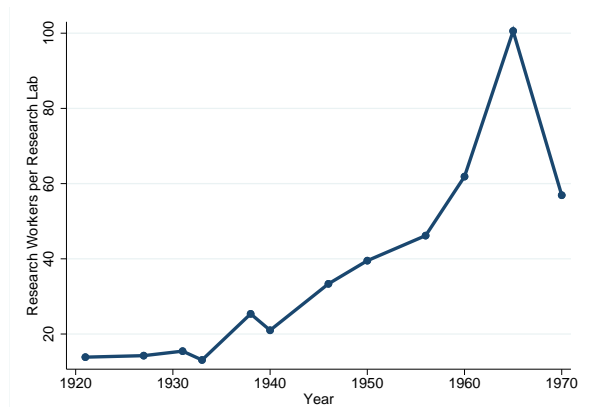
PANEL E: MEAN RESEARCH WORKERS PER LAB

Notes: Figure plots trends in R&D labs from the National Research Council Surveys of Industrial Research Laboratories of the United States (IRLUS).

Figure 7: Firm Patent Distributions
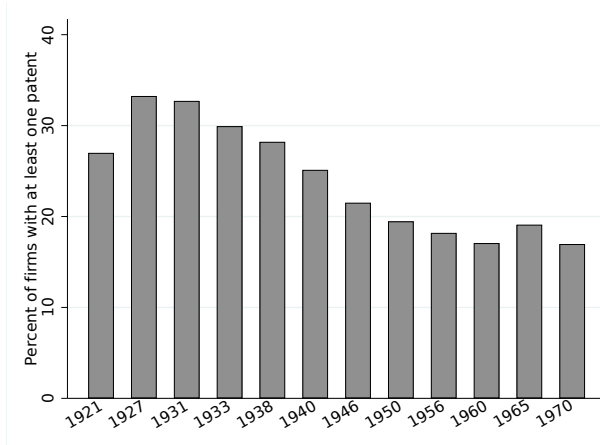
Panel A: % of Firms with Patents

Pr{Patents > 0} = 21.58, Cond. Median = 3, Cond. Mean = 10.28
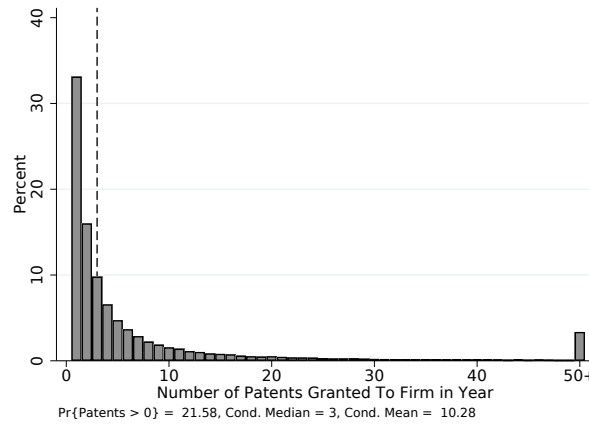
Panel B: Patents per Firm per Year 1920-1970
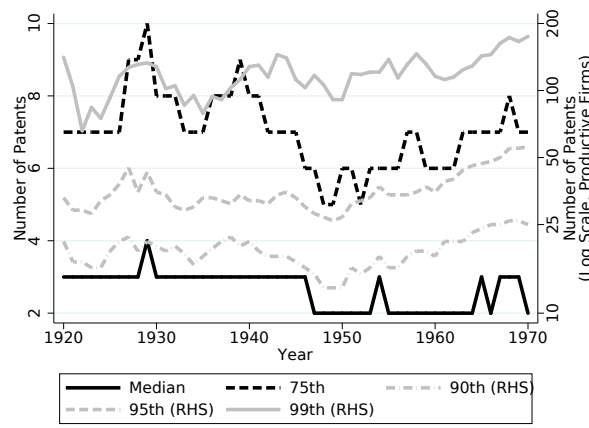
Panel C: Patents per firm over time

Notes: Figure plots distributions of patenting amongst firms with an R&D labs in the National Research Council Surveys of Industrial Research Laboratories of the United States (IRLUS). The top panel plots the share of firms in each survey year which have at least one patent in that year. Panel B plots the distribution of firm patenting per year over the R&D lab sample of 1920-1970, conditional on the firm having at least one patent. Panel C plots the time series of the firm-year level patenting distribution, conditional on having at least one patent.

FIGURE 8: INTRODUCTION YEAR OF STATE PERSONAL INCOME TAXES
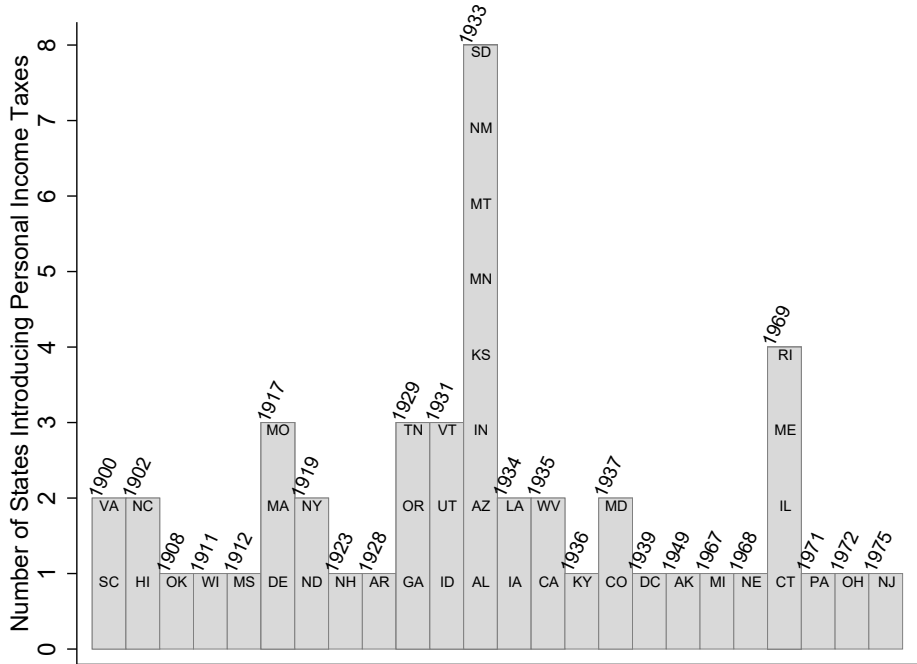
Notes: Figure plots the first year in which each state has a statutory personal income tax rate.

FIGURE 9: THE EVOLUTION OF PERSONAL INCOME TAXES
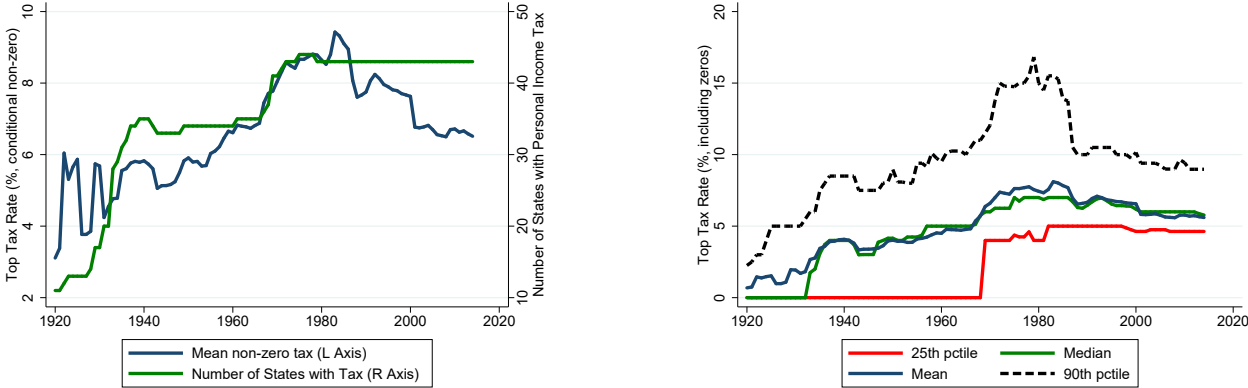
PANEL A: INTENSIVE AND EXTENSIVE MARGIN   PANEL B: DISTRIBUTION OF STATUTORY TAX RATES

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

65

FIGURE 10: TRENDS IN NUMBER OF STATE STATUTORY TAX POLICY CHANGES
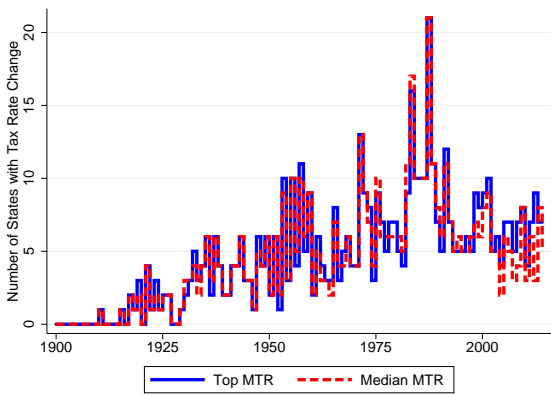
PANEL A: RATE CHANGES
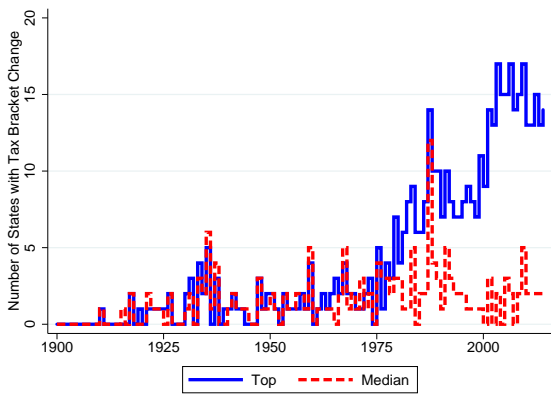
PANEL B: BRACKET CHANGES

Notes: Figure plots the time series of the number of states experiencing a statutory personal income tax rate (panel A) and bracket (panel B) change. The blue line shows the number of states that have a top statutory tax rate or bracket change, while the dashed red line shows the number of states that change the tax rate or bracket for a median earner.

FIGURE 11: MARGINAL TAX RATES AT THE MEDIAN INCOME OVER TIME

PANEL A: 1940
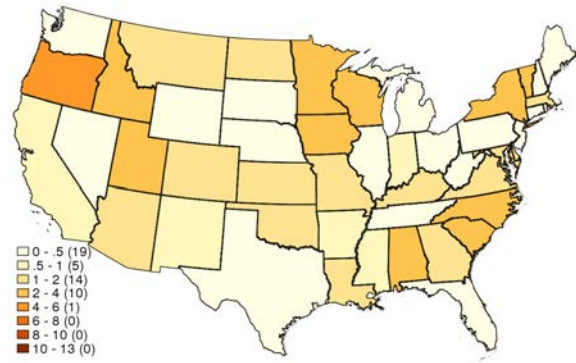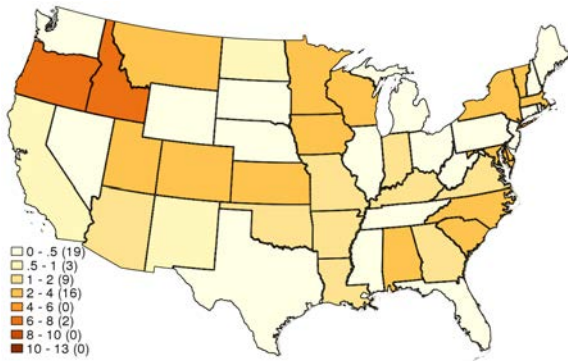
PANEL B: 1950

PANEL C: 1960

PANEL D: 1970
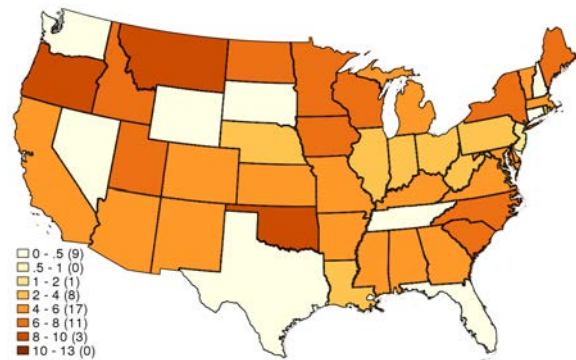
PANEL E: 1980
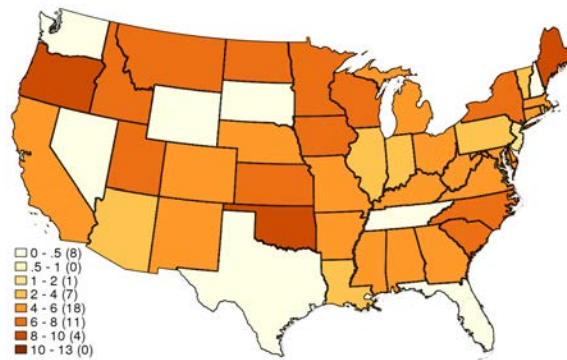
PANEL F: 1990

PANEL G: 2000

FIGURE 12: MARGINAL TAX RATES AT 90th INCOME PERCENTILE OVER TIME
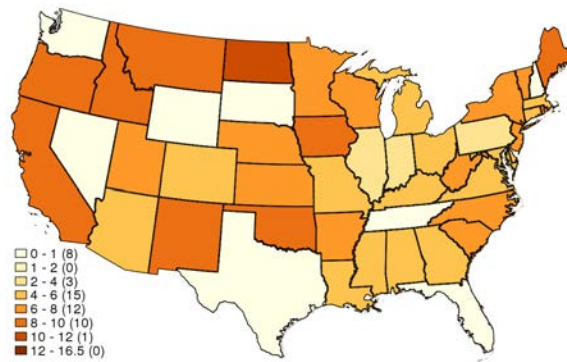
PANEL A: 1940
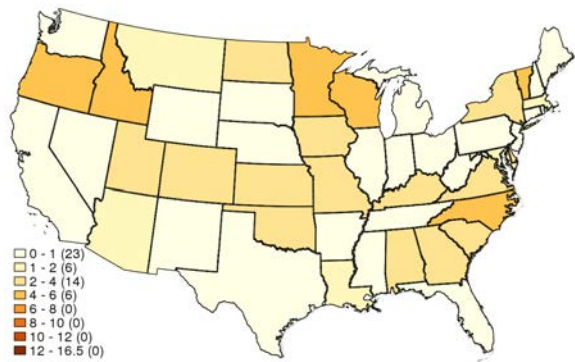
PANEL B: 1950
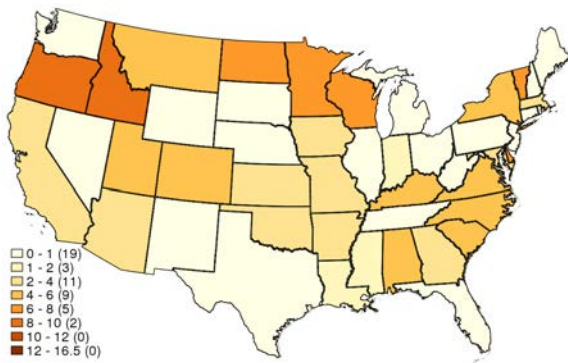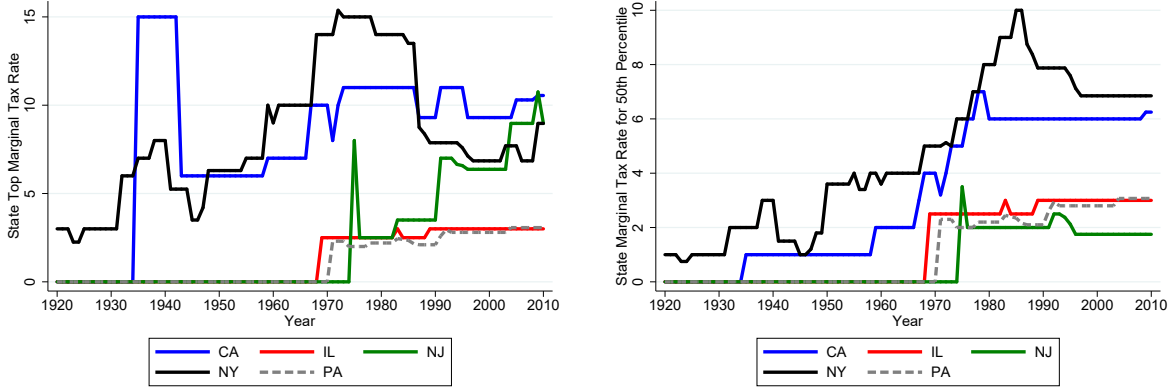
PANEL C: 1960
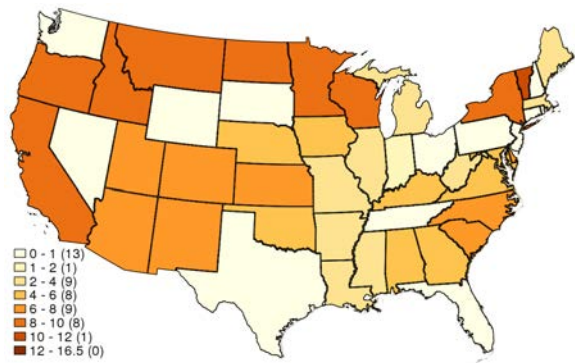
PANEL D: 1970
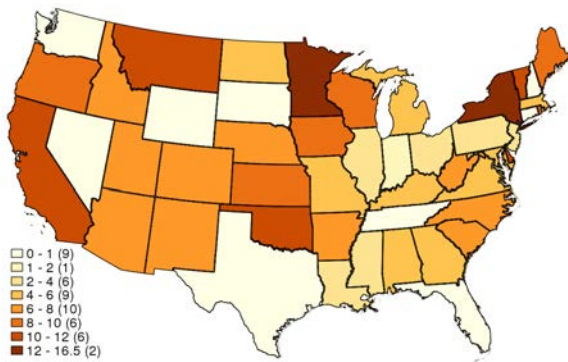
PANEL E: 1980
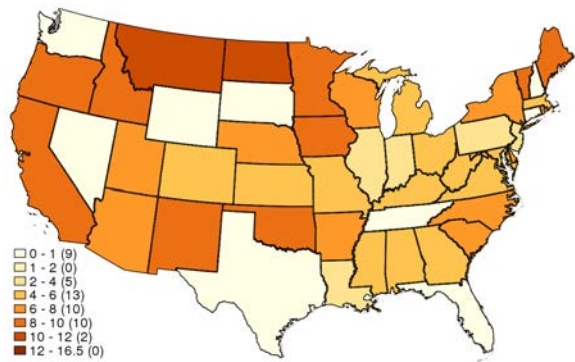
PANEL F: 1990

PANEL G: 2000

FIGURE 13: THE EVOLUTION OF PERSONAL INCOME TAXES IN SELECT STATES
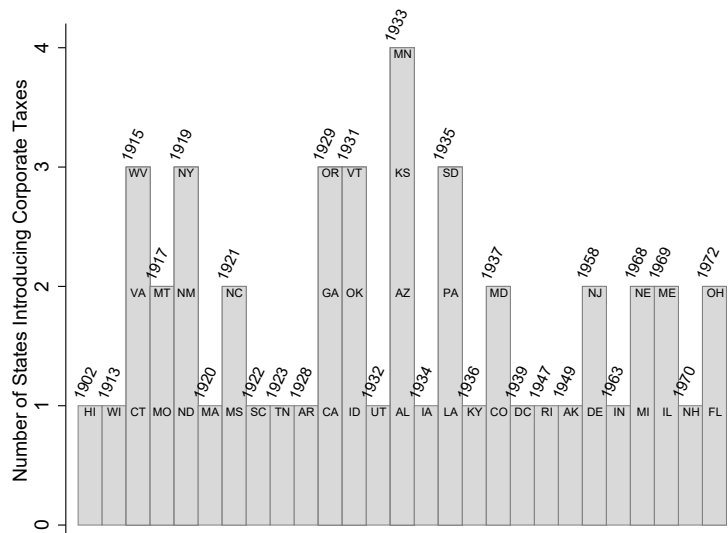

PANEL A: TIME SERIES OF KEY STATES'
TOP STATUTORY MTR

PANEL B: TIME SERIES OF KEY STATES'
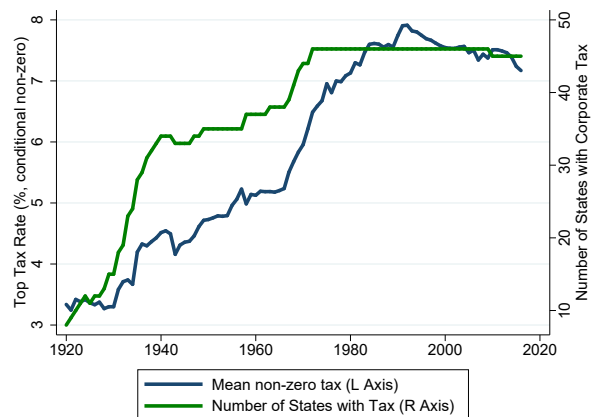MTR FOR MEDIAN EARNER

Notes: Figure plots the time series of marginal personal income tax rates for the five most innovative states in our sample.

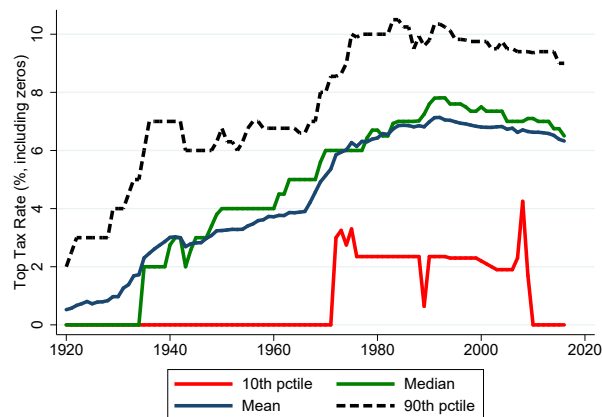FIGURE 14: INTRODUCTION OF STATE CORPORATE TAXES

Notes: Figure plots the first year in which each state has a statutory corporate income tax rate.
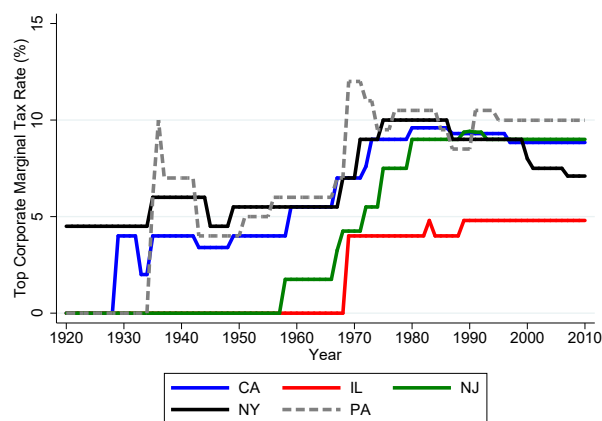
FIGURE 15: THE EVOLUTION OF CORPORATE TAXES

PANEL A: INTENSIVE AND EXTENSIVE MARGIN


PANEL B: DISTRIBUTION OF STATUTORY TAX RATES

PANEL C: TIME SERIES OF SELECT STATES

Notes: Figure plots the time series of the distribution and proliferation of state corporate tax rates. Panel A shows the number of states with a corporate income tax and the mean non-zero tax rate. Panel B plots the distribution of top state corporate tax rates over time. Panel C shows the evolution of top state corporate tax rates for the five most innovative states in our sample.
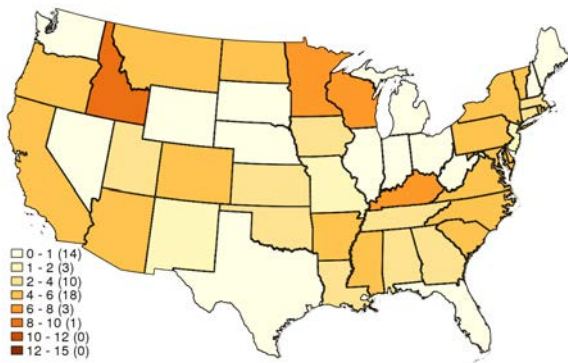
FIGURE 16: TOP STATE CORPORATE MARGINAL TAX RATES OVER TIME
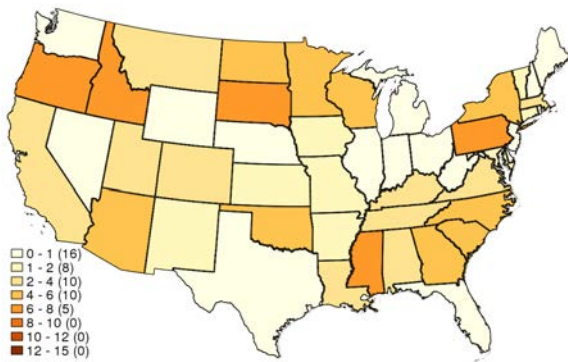
PANEL A: 1940
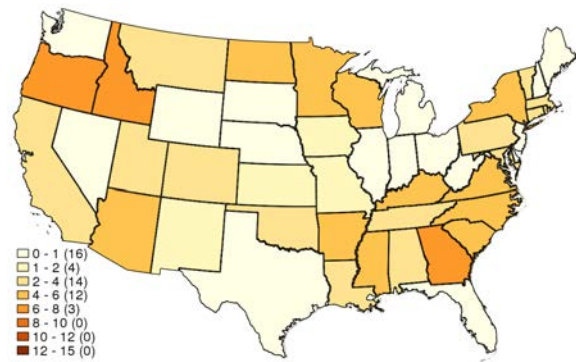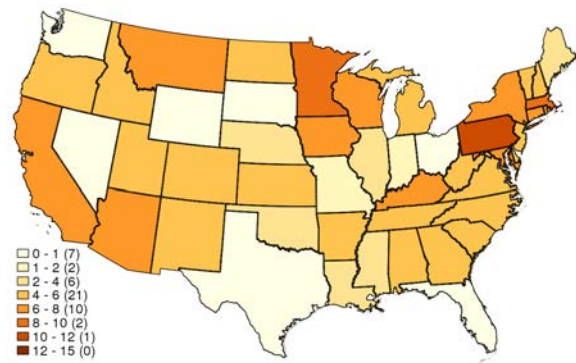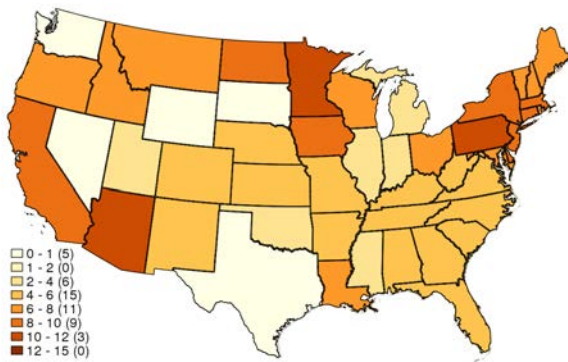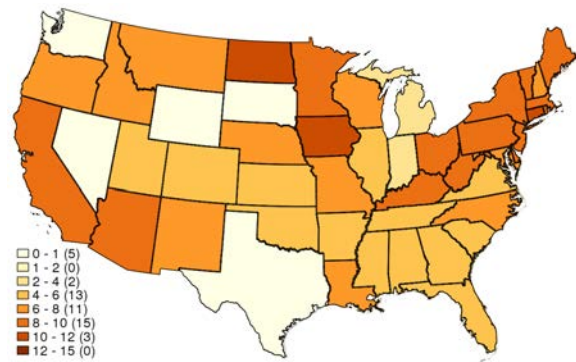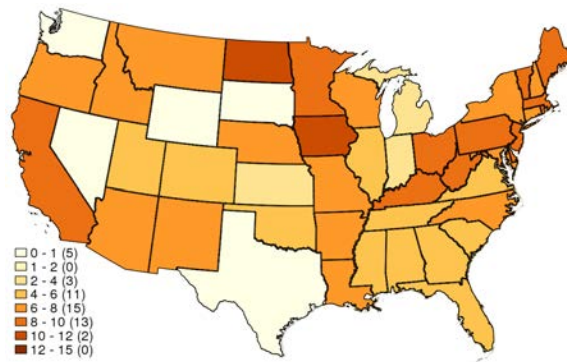
PANEL B: 1950

PANEL C: 1960

PANEL D: 1970

PANEL E: 1980

PANEL F: 1990

PANEL G: 2000

Top 3 synthetic control states: CA (1.000), OR (0.000), FL (0.000)

Top 3 synthetic control states: CA (1.000), TN (0.000), NE (0.000)

Top 3 synthetic control states: CA (1.000), VT (0.000), MD (0.000)
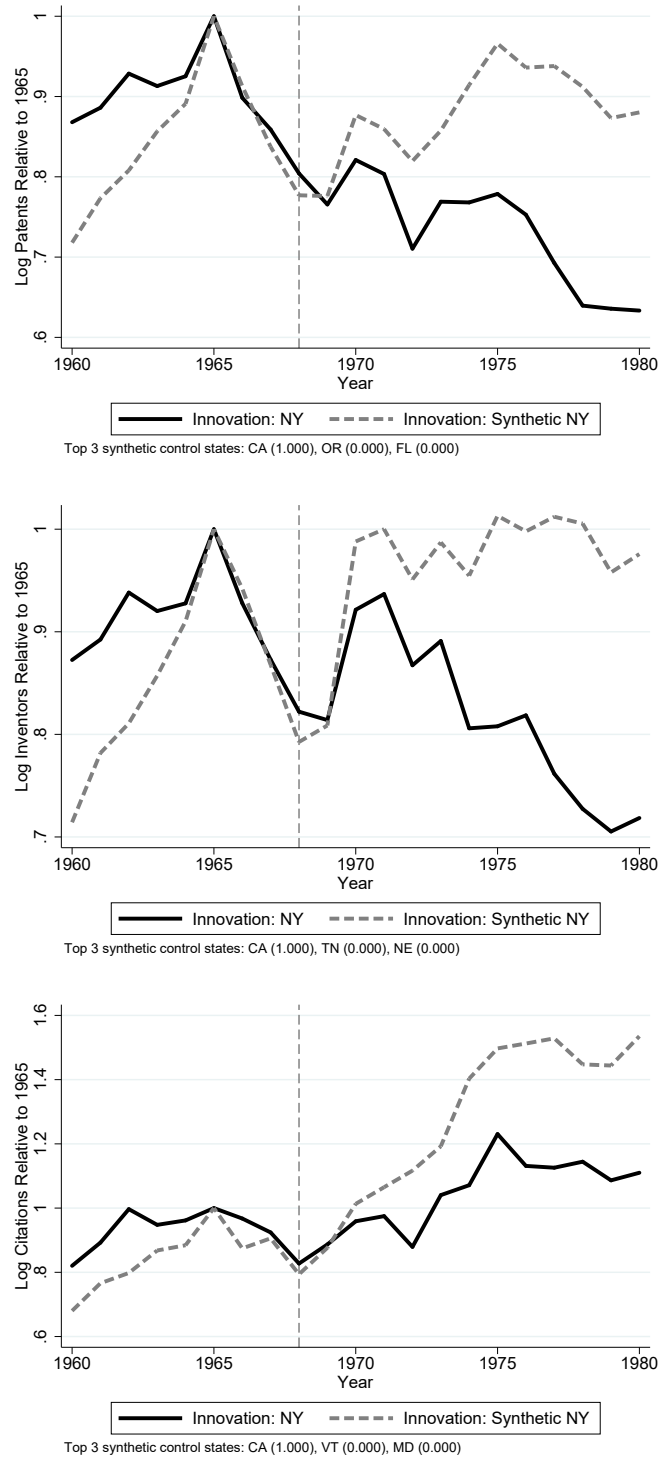
Notes: Figure plots synthetic control analyses for New York's 1968 tax reform bill, in which the top marginal personal income tax rate increased from 10% to 14%, and its state corporate tax rate increased from 5.5% to 7%. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations. We normalize the patent counts for synthetic and actual New York to be the same in 1965.
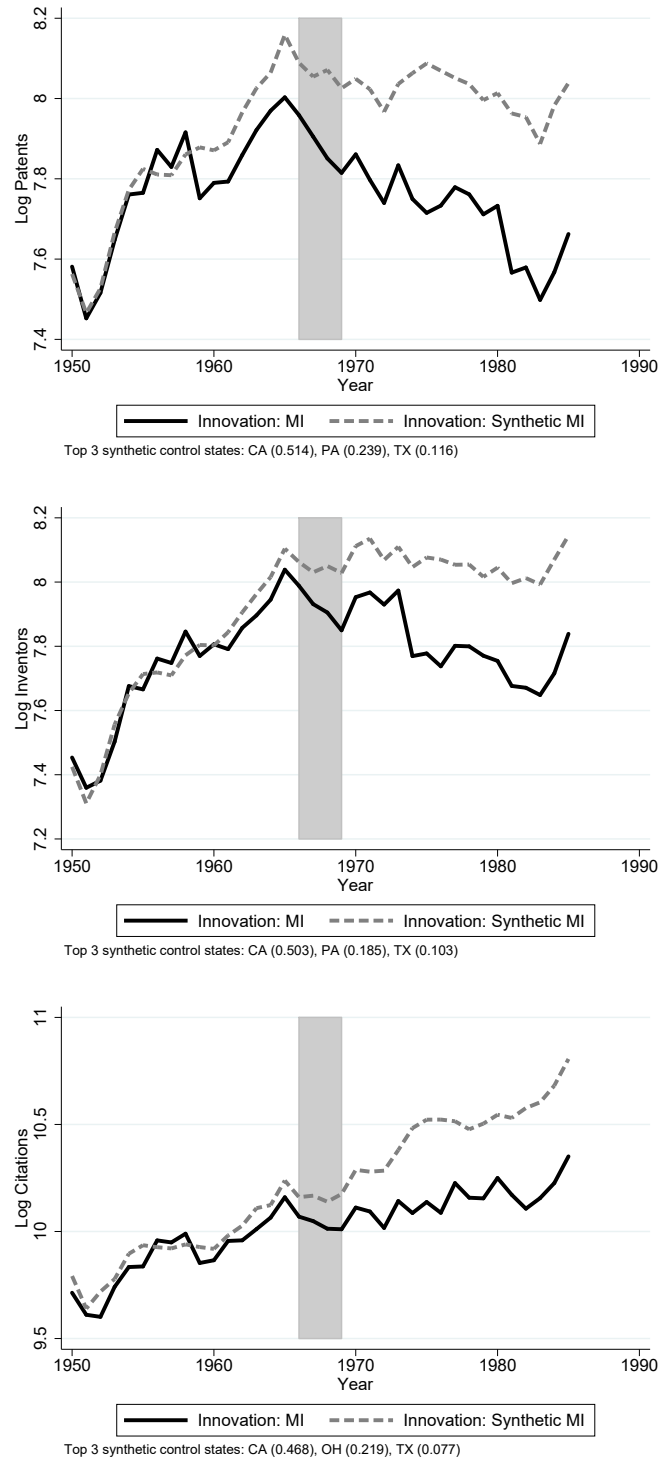
Notes: Figure plots synthetic control analyses Michigan around its major reforms in 1967 and 1968. In 1967, Michigan introduced its personal income tax, at a rate of 2.6%. In 1968, it then introduced its corporate income tax, at a rate of 5.6%. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations.

FIGURE 19: SYNTHETIC CONTROL ANALYSIS: DELAWARE 1970-71
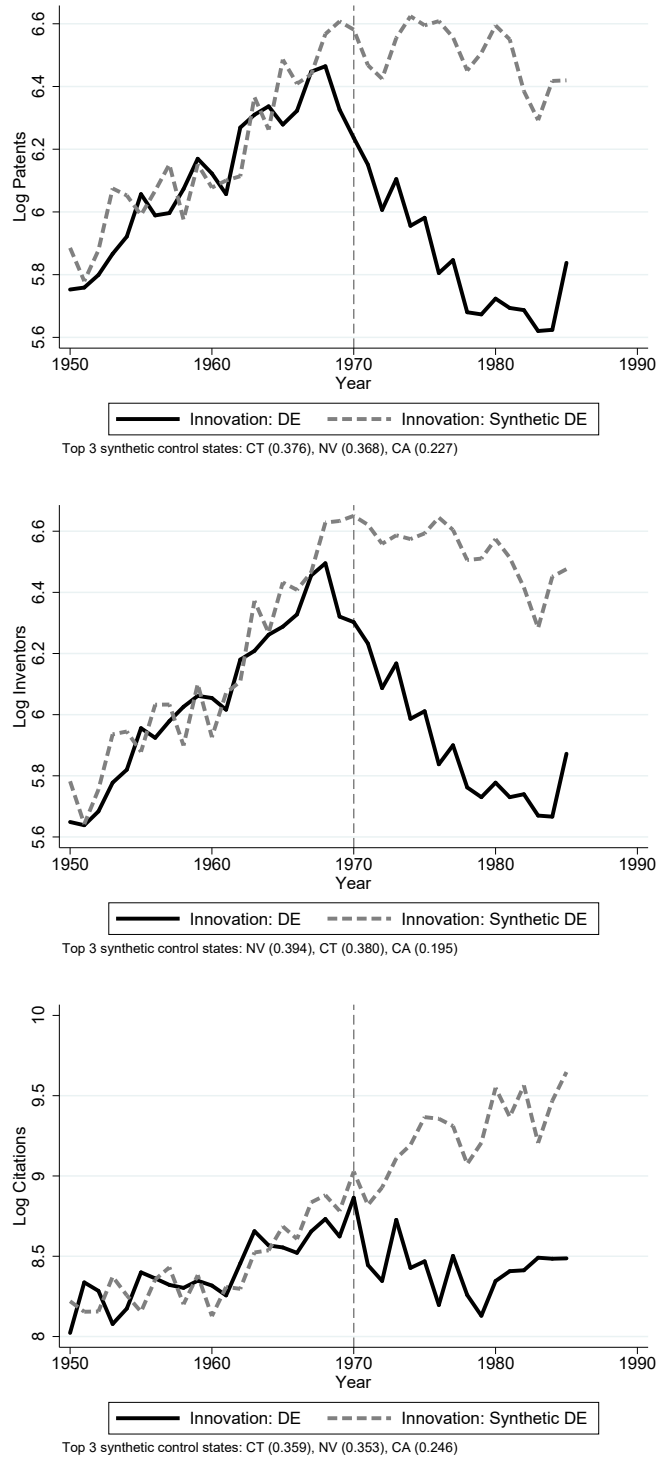
Notes: Figure plots synthetic control analyses around Delaware's 1970 tax reform, in which it increased its corporate income tax rate by 1 percentage point, and followed that by increasing its top personal income tax rate from 11% to 18% in 1971. The first row shows the patterns for log patents, the middle row for log inventors, and the bottom row for log citations.

FIGURE 20: BINNED SCATTER PLOTS: STATE REGRESSIONS
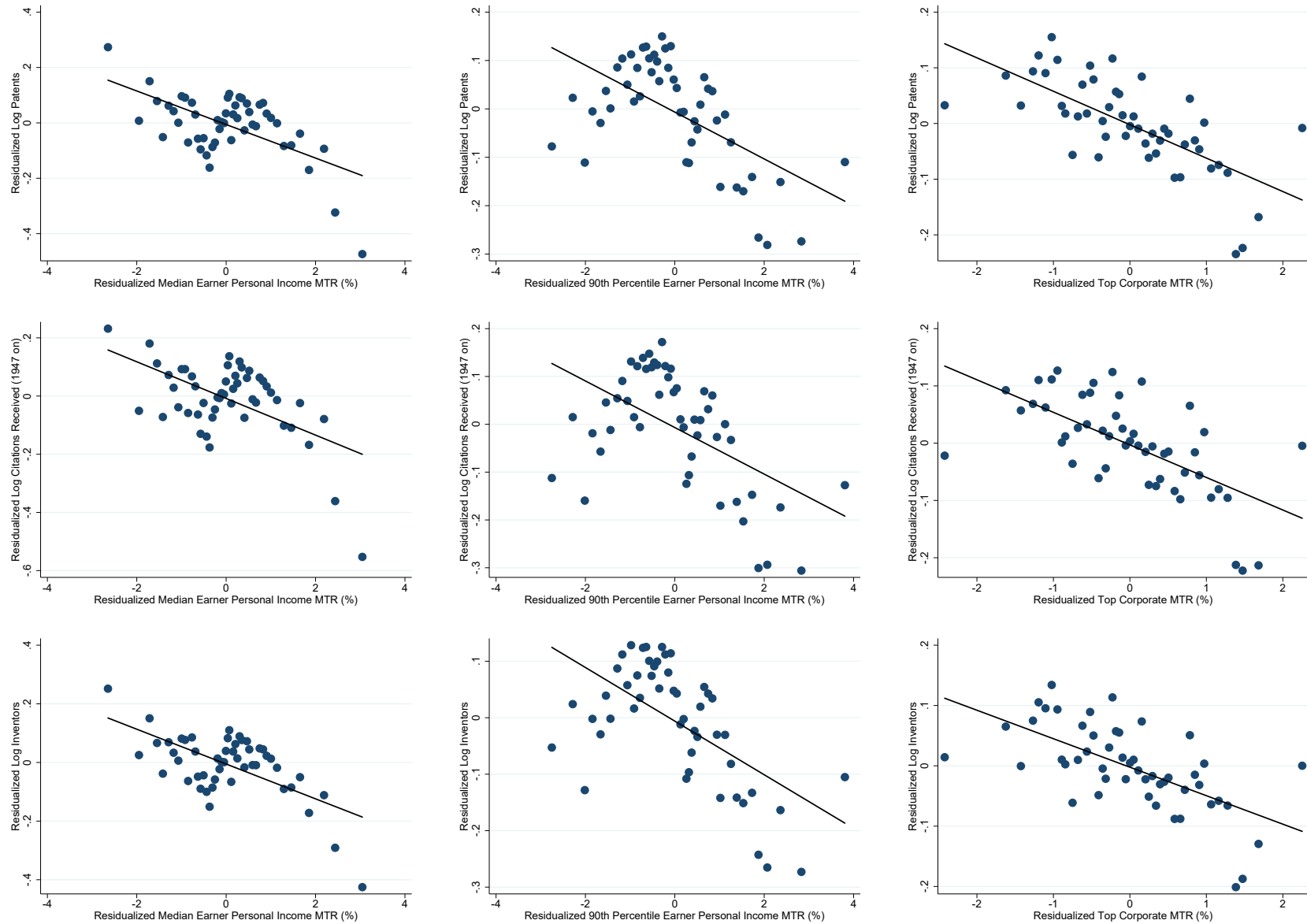
Notes: Figure plots binned scatter plots of effect of taxes at state level. The top row shows the effect on log patents, the middle row present scatters for log citations, while the bottom row shows log inventors. The leftmost column shows the effect of median income marginal tax rates, the middle column shows the effect of MTRs for the 90th percentile earners, and the rightmost column show effect of top corporate MTRs. All tax rates include both federal and state taxes. Both the horizontal and vertical axes are residualized against state and year fixed effects, as well as lagged population density, GDP per capita, and R&D tax credits.

APPENDIX

A.1 Variable Definitions

In this section, we detail the construction of relevant variables for our analysis. All state-level variables have analogous definitions at the county-level for our border-county analysis.

- *Top Corporate Marginal Tax Rate (MTR)* - The additional tax burden accruing to a firm in the top tax bracket in state s for an additional one dollar of revenue if all of its operations were in s. In firm-level regressions (Table 16), we assign firms the average corporate tax in states in which the firm operates an R&D lab, weighted by the share of labs in that state.

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

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

- *Median Income Marginal Tax Rate (MTR)* - The additional tax burden accruing to an individual at the 50th percentile of the national income distribution for an additional one dollar of earnings. Calculated using the tax calculator by Bakija (2017).

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

- *Inventor productivity* - An inventor's productivity in year t is defined to be the number of eventually-granted patents that the inventor has applied for as of year $t-1$. In robustness table A7, inventor i's productivity in year t is defined to be the total number of citations ever received by patents applied for by i through year t. An inventor is said to be "high productivity" in year t if he/she is in the top 10% of the national inventor productivity distribution in year t. In robustness table A4, an inventor is said to be high productivity if he/she is in the top 5% of the national productivity distribution in year t. In robustness table A6, an inventor is said to be high productivity if he/she is *ever* in the top 10% of the national productivity distribution in a single year. Finally, robustness table A8 allows an inventor to be high productivity if he/she is in the top 10% of the productivity distribution, of middle productivity if he/she is between the 75th and 90th percentile of the productivity distribution, and low productivity otherwise.

- *Effective Tax Rates* - An inventor's effective marginal (average) tax rate is defined to be the marginal (average) tax rate faced by the 90th percentile earner in the national income distribution if the inventor is high productivity, and the marginal (average) tax rate faced by a median earner if the inventor is low productivity. In appendix table A8, middle productivity inventors have an effective tax rate equal to the tax rate faced by an individual earning at the 75th percentile of the national income distribution. In all regressions, we use lagged effective tax rates as independent variables. Thus an inventor living in state s will face an effective tax rate for innovation output in year t which is the effective tax rate the inventor would have faced in year $t-1$ given his/her $t-1$ productivity level and the tax laws in place in year $t-1$.

- *Log Patents* - The natural logarithm of the number of eventually-granted patents applied for in state s in year t. Similarly, in firm regressions (Table 16), Log Patents refers to the natural logarithm of the number of successful patent applications for firm j in year t.

- *Log Citations* - The natural logarithm of the number of citations ever received by eventually-granted patents which were applied for in state s in year t. Similarly, in firm regressions (Table 16), Log Citations refers to the natural logarithm of the number of citations ever received by eventually-granted patents which were applied for by firm j in year t. Citation counts adjusted according to the algorithm of Hall et al. (2001), detailed for our data in Akcigit et al. (2017) Appendix B.1.

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

- *Log Superstars* - The natural logarithm of the number of inventors in state s in year t who are in the top 5% of the national inventor productivity distribution.

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

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

- *Log Patents (3-year)* - The log of the number of eventually-granted patents applied for by inventor i years t through $t+2$.

- *Log Citations (3-year)* - The log of the number of citations ever received by eventually-granted patents which were applied for by inventor i years t through $t+2$. Citation counts adjusted according to the algorithm of Hall et al. (2001), detailed for our data in Akcigit et al. (2017) Appendix B.1.

- *Has Patent (3-year)* - An indicator variable, equal to 100 (for legibility) if the inventor has at least one successful patent application between years t and $t + 2$. Inventors are included in the regression sample for the period between their first ever successful patent application, and their last ever successful patent application.

- *Has 10+ Cites (3-year)* - An indicator variable, equal to 100 (for legibility) if the inventor's patents, applied for between years t and $t+2$, ever receive at least 10 citations in total between them. Inventors are included in the regression sample for the period between their first ever successful patent application, and their last ever successful patent application. Patent citation counts adjusted according to the algorithm of Hall et al. (2001), detailed for our data in Akcigit et al. (2017) Appendix B.1.

- *Has Corporate Patent (3-yr)* - An indicator variable, equal to 100 (for legibility) if the inventor successfully applies for at least one patent, which is assigned to a corporation, between years t and $t + 2$. Inventors are included in the regression sample for the period between their first ever successful patent application, and their last ever successful patent application.

- *Corporate Inventor* - An inventor is said to be a corporate inventor if he/she is granted at least one corporate patent in his/her career.

- *# of Research Workers* - The number of research workers employed by the firm as stated on the National Research Council (NRC) Surveys of *Industrial Research Laboratories of the United States* (IRLUS).

- *Agglomeration* - The number of patents, in thousands, applied for by inventors $j \neq i$ who share inventor i's modal patent class in year t in state s.

- *Mover* - An inventor is said to be a mover if he/she applies for patents in at least two states over the sample period. Analagously, non-movers are those inventors who only apply for patents in one state over the entire course of their career.

- *Home State* - The state in which an inventor first applies for a patent.

- *Assignee Has Patent in Destination* - An indicator variable equal to one if an inventor i's firm has at least one patent applied for in year t by an inventor $j \neq i$ in destination state s.

- *Inventor Tenure/Experience* - an inventor's tenure is the number of years that have passed since the inventor's first successful patent application.

A.2   Additional Tables and Figures

TABLE A1: MACRO EFFECTS OF TAXES: STATE LEVEL REGRESSIONS, EXCLUDING FEDERAL TAXES

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Log Superstars (4)	Citations/ Patent (5)	Share Assigned (6)
90th Pctile Income MTR	-0.026***	-0.021***	-0.027***	-0.028***	0.188***	-0.018
	(0.002)	(0.003)	(0.002)	(0.004)	(0.042)	(0.065)
Top Corporate MTR	-0.053***	-0.056***	-0.045***	-0.077***	-0.231***	-0.799***
	(0.008)	(0.009)	(0.007)	(0.011)	(0.056)	(0.142)
Median Income MTR	-0.042***	-0.041***	-0.042***	-0.056***	0.087	-0.085
	(0.004)	(0.004)	(0.004)	(0.006)	(0.053)	(0.090)
Top Corporate MTR	-0.055***	-0.056***	-0.048***	-0.077***	-0.176***	-0.790***
	(0.008)	(0.009)	(0.007)	(0.011)	(0.048)	(0.135)
90th Pctile Income ATR	-0.047***	-0.040***	-0.046***	-0.060***	0.232***	-0.011
	(0.003)	(0.004)	(0.003)	(0.006)	(0.056)	(0.093)
Top Corporate MTR	-0.053***	-0.055***	-0.046***	-0.074***	-0.210***	-0.803***
	(0.008)	(0.009)	(0.007)	(0.011)	(0.051)	(0.139)
Median Income ATR	-0.095***	-0.102***	-0.086***	-0.144***	-0.541***	-0.691***
	(0.008)	(0.010)	(0.007)	(0.010)	(0.129)	(0.143)
Top Corporate MTR	-0.054***	-0.054***	-0.047***	-0.074***	-0.108**	-0.739***
	(0.008)	(0.008)	(0.007)	(0.010)	(0.043)	(0.125)
Observations	2867	2867	2867	2661	2867	2867
Mean of Dep. Var.	7.18	9.87	7.31	4.37	17.68	71.74
S.D. of Dep. Var.	1.31	1.59	1.33	1.60	12.48	14.01

Notes: The period covered is 1940-2000. White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state and year fixed effects. Tax rates measured in percentage points and lagged by 1 year. Only state tax rates included in tax measures.

TABLE A2: THE MACRO EFFECT OF TAXATION: ESTIMATES FROM STATE LEVEL RE-
GRESSIONS, EXCLUDING CALIFORNIA

	Log Patents (1)	Log Citations (2)	Log Inventors (3)	Log Superstars (4)	Citations/ Patent (5)	Share Assigned (6)
90th Pctile Income MTR	-0.055***	-0.052***	-0.053***	-0.063***	-0.001	-0.390***
	(0.005)	(0.006)	(0.005)	(0.008)	(0.058)	(0.072)
Top Corporate MTR	-0.056***	-0.050***	-0.045***	-0.083***	0.156**	-1.007***
	(0.006)	(0.007)	(0.006)	(0.010)	(0.066)	(0.146)
Median Income MTR	-0.076***	-0.083***	-0.073***	-0.097***	-0.247***	-0.337***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.080)	(0.086)
Top Corporate MTR	-0.050***	-0.041***	-0.039***	-0.073***	0.233***	-1.026***
	(0.007)	(0.008)	(0.006)	(0.011)	(0.072)	(0.156)
90th Pctile Income ATR	-0.107***	-0.111***	-0.102***	-0.133***	-0.248**	-0.453***
	(0.006)	(0.008)	(0.005)	(0.009)	(0.101)	(0.105)
Top Corporate MTR	-0.041***	-0.033***	-0.031***	-0.064***	0.230***	-0.995***
	(0.006)	(0.007)	(0.006)	(0.010)	(0.078)	(0.155)
Median Income ATR	-0.099***	-0.105***	-0.090***	-0.150***	-0.435***	-0.585***
	(0.007)	(0.010)	(0.007)	(0.010)	(0.126)	(0.144)
Top Corporate MTR	-0.057***	-0.049***	-0.047***	-0.080***	0.227***	-1.035***
	(0.007)	(0.007)	(0.006)	(0.011)	(0.073)	(0.155)
Observations	2806	2806	2806	2600	2806	2806
Mean of Dep. Var.	6.99	9.64	7.12	4.19	16.86	71.97
S.D. of Dep. Var.	1.24	1.48	1.25	1.56	11.51	14.32

Notes: White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state and year fixed effects. Tax rates measured in percentage points and lagged by 1 year. Regressions weighted by state-year level population counts.

FIGURE A1: INVENTORS PER CAPITA OVER TIME
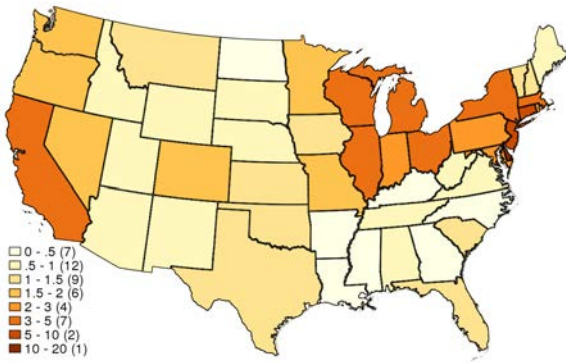
PANEL A: 1940
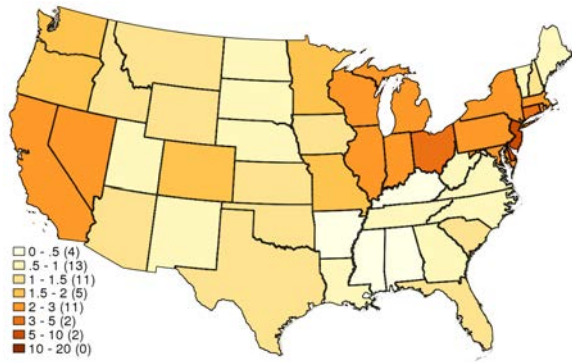
PANEL B: 1950
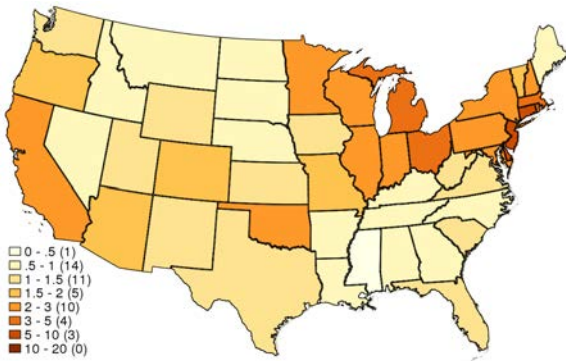
PANEL C: 1960
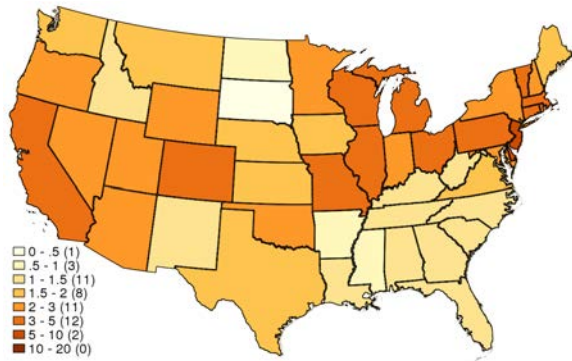
PANEL D: 1970
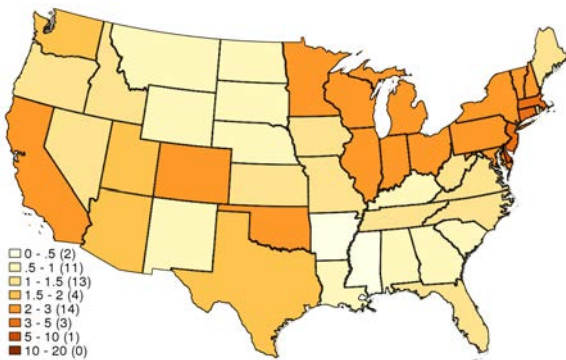
PANEL E: 1980
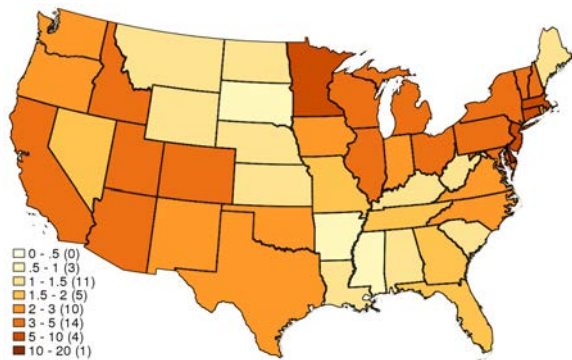
PANEL F: 1990
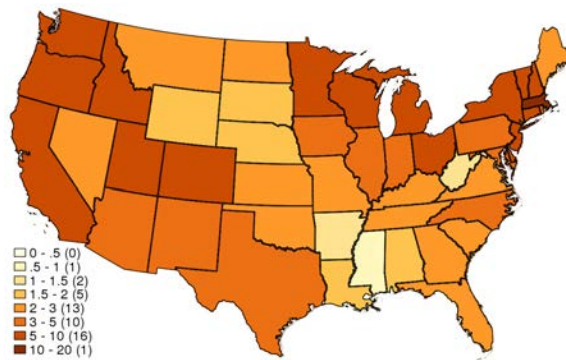
PANEL G: 2000

TABLE A3: MACRO EFFECTS OF TAXES: EXCLUDING MOVERS (OLS)

	Log Patents (1)	Log Citations (2)	Log Inventor (3)	Citations/ Patent (4)	Share Assigned (5)
90th Pctile Income MTR	-0.042***	-0.043***	-0.041***	-0.108**	-0.433***
	(0.005)	(0.005)	(0.004)	(0.051)	(0.074)
Top Corporate MTR	-0.061***	-0.063***	-0.050***	-0.157**	-1.091***
	(0.006)	(0.008)	(0.006)	(0.061)	(0.148)
Median Income MTR	-0.045***	-0.044***	-0.045***	0.038	-0.195**
	(0.004)	(0.005)	(0.004)	(0.047)	(0.083)
Top Corporate MTR	-0.062***	-0.064***	-0.050***	-0.207***	-1.183***
	(0.008)	(0.009)	(0.007)	(0.068)	(0.162)
90th Pctile Income ATR	-0.064***	-0.060***	-0.062***	0.079	-0.321***
	(0.004)	(0.005)	(0.004)	(0.053)	(0.094)
Top Corporate MTR	-0.056***	-0.059***	-0.044***	-0.220***	-1.144***
	(0.007)	(0.008)	(0.006)	(0.064)	(0.161)
Median Income ATR	-0.095***	-0.103***	-0.088***	-0.554***	-0.905***
	(0.007)	(0.010)	(0.007)	(0.126)	(0.141)
Top Corporate MTR	-0.060***	-0.061***	-0.049***	-0.102	-1.092***
	(0.007)	(0.008)	(0.006)	(0.061)	(0.151)
Observations	2867	2867	2867	2867	2867
Mean of Dep. Var.	6.90	9.56	7.11	16.85	68.40
S.D. of Dep. Var.	1.30	1.57	1.32	11.31	14.66

Notes: White heteroskedasticity robust standard errors clustered at year level reported in parentheses. All regressions include controls for lagged population density, real GDP per capita, and R&D tax credits, as well as state and year fixed effects. Tax rates measured in percentage points and lagged by 1 year. Regressions weighted by state-year level population counts.

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)	Has Corporate Patent (3-yr)
	(1)	(2)	(3)	(4)	(5)
Effective MTR	-0.625***	-0.624***	-0.013***	-0.017***	-0.674***
	(0.092)	(0.103)	(0.003)	(0.003)	(0.081)
Top Corporate MTR	-0.064	-0.076	-0.002	-0.003	-0.047
	(0.050)	(0.058)	(0.001)	(0.002)	(0.047)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.618***	-0.600***	-0.011***	-0.012***	-0.656***
	(0.104)	(0.117)	(0.004)	(0.004)	(0.092)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5964243	5964243	4550168	4396954	5964243
Mean of Dep. Var.	76.291	45.069	0.442	2.758	61.399
S.D. of Dep. Var.	42.530	49.756	0.664	1.453	48.683

Notes: Standard errors clustered at year level reported in parentheses. Only state-years undergoing progressive spells included. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Inventor productivity defined as being in the top 5% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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 in the state.

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)	Has Corporate Patent (3-yr)
	(1)	(2)	(3)	(4)	(5)
Effective MTR	-0.390***	-0.453***	-0.010***	-0.014***	-0.501***
	(0.086)	(0.100)	(0.003)	(0.003)	(0.068)
Top Corporate MTR	-0.023	0.064	-0.004	0.001	0.020
	(0.117)	(0.114)	(0.003)	(0.004)	(0.120)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.425***	-0.449***	-0.008***	-0.011***	-0.509***
	(0.090)	(0.102)	(0.003)	(0.003)	(0.069)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	2759975	2759975	2095175	2027602	2759975
Mean of Dep. Var.	75.913	45.713	0.447	2.814	59.769
S.D. of Dep. Var.	42.761	49.816	0.672	1.484	49.036

Notes: Standard errors clustered at year level reported in parentheses. Only state-years undergoing progressive spells included. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Inventor productivity defined as being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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 in the state.

Dependent Variable:	Has Patent (3-year) (1)	Has 10+ Cites (3-year) (2)	Log Patents (3-year) (3)	Log Citations (3-year) (4)	Has Corporate Patent (3-yr) (5)
Effective MTR	-0.835***	-0.532***	-0.012***	-0.013***	-0.559***
	(0.153)	(0.101)	(0.003)	(0.004)	(0.098)
Top Corporate MTR	-0.131	-0.109	-0.001	-0.001	-0.095
	(0.114)	(0.102)	(0.002)	(0.003)	(0.096)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.856***	-0.473***	-0.010**	-0.010	-0.512***
	(0.172)	(0.127)	(0.004)	(0.006)	(0.116)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5960430	5960430	4548136	4394979	5960430
Mean of Dep. Var.	76.306	45.078	0.442	2.758	61.407
S.D. of Dep. Var.	42.521	49.757	0.664	1.454	48.681

Notes: Standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Inventor productivity defined as ever being in the top 10% of dynamic patent counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions control for local agglomeration forces, measured as the number of patents applied for in the inventor's modal class in state s in year $t - 1$ by other residents in the state.

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)	Has Corporate Patent (3-yr)
	(1)	(2)	(3)	(4)	(5)
Effective MTR	-0.467***	-0.458***	-0.009***	-0.015***	-0.515***
	(0.097)	(0.121)	(0.003)	(0.003)	(0.076)
Top Corporate MTR	-0.243**	-0.144	-0.003*	-0.001	-0.131
	(0.101)	(0.100)	(0.002)	(0.002)	(0.091)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.425***	-0.394***	-0.007**	-0.012***	-0.456***
	(0.101)	(0.131)	(0.003)	(0.003)	(0.079)
State × Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	5960430	5960430	4548136	4394979	5960430
Mean of Dep. Var.	76.306	45.078	0.442	2.758	61.407
S.D. of Dep. Var.	42.521	49.757	0.664	1.454	48.681

Notes: Standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes 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 rate faced by the median earner for low productivity inventors. Inventor productivity defined as being in the top 10% of dynamic citation counts. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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 in the state.

TABLE A8: MICRO REGRESSION COEFFICIENTS: THREE PRODUCTIVITY CUTOFFS

Dependent Variable:	Has Patent (3-year)	Has 10+ Cites (3-year)	Log Patents (3-year)	Log Citations (3-year)	Has Corporate Patent (3-yr)
	(1)	(2)	(3)	(4)	(5)
Effective MTR	-0.629***	-0.563***	-0.011***	-0.016***	-0.587***
	(0.102)	(0.072)	(0.001)	(0.001)	(0.072)
Top Corporate MTR	-0.202**	-0.104	-0.002*	-0.002	-0.059
	(0.090)	(0.074)	(0.001)	(0.002)	(0.078)
State FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Effective MTR	-0.791***	-0.661***	-0.012***	-0.017***	-0.682***
	(0.130)	(0.090)	(0.002)	(0.002)	(0.089)
State $\times$ Year FE	Y	Y	Y	Y	Y
Inventor FE	Y	Y	Y	Y	Y
Observations	3940182	3940182	2541638	2465129	3940182
Mean of Dep. Var.	64.644	41.771	0.614	2.972	54.645
S.D. of Dep. Var.	47.807	49.318	0.742	1.505	49.784

Notes: Standard errors clustered at year level reported in parentheses. All mainland states, excluding Louisiana, included for the period 1940-2000. All tax rates on percentage point scale, and lagged by one year. Effective taxes defined as the marginal tax rate faced by the 90th percentile earner in state s in year t for high productivity inventors, the rate faced by the 75th percentile earner for mid-productivity inventors, and the marginal tax rate rate faced by the median earner for low productivity inventors. Inventors are said to be high, or middle productivity if they are above the 10th, or 25th percentiles of dynamic patent counts, and low productivity otherwise. Regressions with state and year fixed effects include controls for lagged real state GDP per capita, population density, and a quadratic in inventor tenure. All regressions include controls for inventor productivity, 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 in the state.

ONLINE APPENDIX – NOT FOR PUBLICATION

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

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

OA.1 Disambiguation Algorithm

We employ the algorithm of Lai et al. (2014) to disambiguate inventors in our historical patent data.[19] The goal of disambiguation is to determine if two patent-inventor level records were produced by the same inventor. A problem of this sort may be distilled into a clustering problem well-suited to standard machine learning algorithms: given a training dataset and a set of features – such as inventor name, location, technology class, assignee, and coauthor networks – we wish to group records together into profiles which indicate that the two records were produced by the same inventor. The goal is to assign probabilities of an inventor match based on the characteristics of every pair of observations. The central idea is that two records coming from two very similar names (not necessarily identical: "John A Smith" vs "John Adam Smith" for instance) working in similar subject areas, working for the same company in roughly the same geographic location, are likely to be the same person.

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

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

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

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

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

Our baseline approach lies somewhere in between these two strategies. We use the matches of Lai et al. to form the basis of our training dataset. We draw twenty million pairs of records belonging to different inventors according to Lai et al. to complete our training dataset. Using this as a training dataset relies on two principal assumptions: first, we assume that the Lai et al. disambiguation correctly identifies inventors, and second we assume that the sets of features that were predictive of inventor clustering are stable over time, so that the same rules for determining matches in the modern sample of Lai et al. will apply to our historical sample. We choose this approach in order to best match the state-of-the-art disambiguation of inventors in the modern data.[20]

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

Our starting point is the historical inventor data digitized by Akcigit et al. (2017), combined with the patent data of Lai et al. (2014) available on the Harvard Dataverse Network (HDN).[21] We first manually clean inventor names and location to correct for obvious typos. The most common correction is to remove prefixes and suffixes, such as "DR," "JR," and "SR." In addition, we standardize names to be all capital letters, and consider a person's first name to be the first word of their name. Finally, we consider only the first patent class listed on a patent document to be

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

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

that patent's primary classification.

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

- First and Last names

    1. If one of the two records is missing the name

    2. If there is no clear misspelling or abbreviation employed, and the strings do not exactly match

    3. If there is a misspelling (defined as either missing 1 or 2 characters somewhere, or switching the place of a few characters)

    4. If exact match or, in the case of first names, if one string appears to be an abbreviation of the other in that it has the first 3 characters the same (e.g. "ROB" and "ROBERT")

- Middle Names

    0. If have different middle names

    1. If one of the two records have missing middle name

    2. If both records have missing middle name

    3. If one record has a full middle name (e.g. "WILLIAM") and the other has just the middle initial which matches the full middle name (e.g. "W").

    4. If exactly the same name

- Location

    1. If over 50 miles apart

    2. If under 50 miles apart

    3. If under 25 miles apart

    4. If under 10 miles apart

    5. If under 1 mile apart

- Patent Classes

    0. If different strings

    1. If exactly the same string

- Assignees

    5. If the Jaro-Winkler string distance between assignee names is at least 0.9

4. If JW distance > 0.8

3. If JW distance > 0.7

2. If one of the two records has a missing assignee

1. Otherwise

- Coauthors

    1. If coauthors exactly the same (coauthors entered as <First Initial> . <Last Name> and separated by comma in the variable)

    0. Otherwise

- Country

    0. If different country

    1. If the same non-US country

    2. If the same US country

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

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

where $P(\mathcal{M})$ is the prior probability of a match, which we follow Lai et al. in setting as proportional to the ratio of the number of within-cluster pairs (i.e. disambiguated inventors from prior blocking rounds) in a block to the total number of pairs in that block.[22] For numerical reasons, it is more convenient to work with the posterior *odds* of a match, defined as

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

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

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

This can be determined directly from the training dataset by comparing the number of records with similarity profile x that belong in the matched training dataset (i.e. come from the same

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

inventor), to the number of records with similarity profile x that belong in the unmatched training dataset (i.e. come from different inventors).[23] Once we have the likelihood ratios calculated, we invert them to calculate the probability that two records originated from the same inventor:

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

We say that two records originated from the same inventor if this posterior probability of a match is at least 0.99.[24]

Our blocking routine proceeds as follows:[25]

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

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

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

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

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

OA.2 Assigning Inventors to States

Our patent data provides information on the residence address of the patent's inventors. However, we do not observe the residence of all inventors on a patent in the historical period. Specifically, we observe an inventor's state if either 1) they are the first inventor on the patent, or 2) the patent is contained in the Harvard Dataverse Network (HDN) data. In order to run our inventor-level

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

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

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

regressions, we must assign each inventor to a particular home state. In this section, we detail our approach to doing so.

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

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

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

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

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

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

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

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

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

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

- Inventors have multiple coauthors, who live in different states and who alternate in terms of who is the first listed author. For instance, Harvey Clayton Rentschler lives in Pittsburgh, PA, but frequently coauthors with J. Marden, who lives in Orange, NJ. Every time they coauthor a patent, the location is listed as Orange, NJ, but every time Harvey Rentschler sole authors a patent, his location appears to be Pittsburgh. These situations are particularly common

among assigned patents, and seem to account for all individuals living in an exceptionally high number of states. Indeed, everyone who shows up in 7 or more states has a coauthor on their patents, while the share of those with a coauthor is 92.8% for those with multiple states, compared with just 66.3% for those in one state[26]

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

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

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

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

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

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

OA.3 Historical Corporate Tax Data

We collected the corporate tax rates from a large variety of sources. We have built a documentation available at https://scholar.harvard.edu/stantcheva/publications that shows all the sources for each year and state. We only collected direct taxes and net income franchise taxes. We also collect surtaxes or surcharges, as well as additional temporary taxes imposed on top of the main rates. They are sometimes imposed as a percentage of regular tax liabilities and sometimes as a rate to add to the main rate. We record them as rates to add to the main rate with applicable thresholds. We have not collected minimum taxes (they are very low and probably not applicable to the companies in our sample) and alternative minimum taxes.

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