Regulating Inventors

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Abstract

I study how regulatory burden disrupts the careers of productive inventors. Using structural topic modeling and the text of compliance regulations, I develop a time-varying inventor-specific measure of regulatory burden. Inventors facing high burden exhibit decreased productivity and lower quality innovations. These results are concentrated in Star Inventors. A 1 standard deviation increase in time spent on compliance decreases Star patenting by 13.9% (14,900 patents annually in aggregate) and scaled citations by 2.8%. These effects are identified within inventor over time, net of employer-city trends, ruling out alternative explanations like time-varying employer innovation strategy or location-specific innovation factors. In terms of labor market outcomes, I find evidence consistent with a disutility channel: after experiencing increases in burden, inventors are more likely to switch jobs, and to seek positions at larger employers. Overall, the findings document the innovation consequences of regulatory burden, influencing both the quantity and quality of patented inventions, and the mobility of inventors.

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1 Introduction

Financial incentives to innovate abound, as technology spurs economic growth. Academic work shows that policymakers can encourage investment in innovation, influence migration of inventors, and reallocate resources to sectors of national interest;[1] these legislative interventions have far-reaching effects. On the other hand, regulation can function as a tax on the time of innovators, and the consequences of this tax are less understood.[2] In this paper, I study the impact of regulatory compliance on innovation, focusing specifically on the human capital component of the innovation production process. I use unsupervised machine learning methods to develop an inventor-specific measure of the time required to comply with paperwork regulations. This measure identifies relevant regulations to an inventor's patenting history and aggregates regulation-level burden to the inventor-year level. I find that increased time spent on regulatory compliance is associated with fewer patents, decreased patent quality, and lower likelihood of breakthrough technologies.

Compliance regulations originate in federal agencies of the United States executive branch. They primarily serve to enforce good conduct among regulated entities, protecting a wide range of government interests. Each regulation undergoes multiple public comment periods, within-agency reviews, and external audits by the Office of Management and Budget (OMB). These groups work to limit the scope of the regulation, and produce accurate compliance costs in terms of hours, number of responses, and dollars. Once finalized, the text and resultant burden estimates are posted to the Code of Federal Regulation (CFR), and periodically audited by the Government Accountability Office.

In the first part of the paper, I train a structural topic model on the text of 25,000 compliance regulations active between 1993 and 2020, and apply this model to the text of over 5 million patents. This procedure identifies overlapping language between a given patent and its

1. See Zucker and Darby (2014), Akcigit et al. (2016), and Moretti and Wilson 2017 for discussion of factors influencing star scientist mobility, and the ramifications of their movements. See Aghion et al. (2015), Acemoglu et al. (2018), Dambra and Gustafson (2021), and Aghion et al. (2023) for discussions of setting government policies (e.g., taxes, subsidies) to reallocate labor and capital towards more productive uses.

2. See Kalmenovitz (2023) and Trebbi et al. (2023) for discussion of the direct costs of compliance in, respectively, U.S. public firms and all establishments in the Occupational Employment and Wage Statistics (OEWS) aurvey from the U.S. Bureau of Labor Statistics (BLS), and Hassan et al. (2019) and Calomiris et al. (2020) for discussion of political and regulatory risk perception by management and ramifications of uncertainty.

relevant regulations, i.e., a topic proportion. I then construct a patent-level estimate of burden from these topic proportions and the government's reported regulation-level burdens. I use an inventor's historical patenting to aggregate these patent-level estimates to the inventor-level, generating an annually-updated, inventor-specific measure of regulatory burden, 'Time Burden'.[3] These estimates increase during expansionary regulatory regimes (e.g., 2009-2016), and are significantly higher in heavily scrutinized industries (e.g., medical devices, nuclear engineering, transportation). They are also positively correlated with other text-based regulatory burden measures, namely the (public) firm-level measures from Kalmenovitz (2023) and the annual CFR measures from Al-Ubaydli and McLaughlin (2017). This procedure can be applied to any actively patenting individual; my sample contains 1.4 million inventors productive between 1993 and 2020.

The distribution of skill across inventors is quite positively skewed. For example, the median inventor in my sample accumulates 14 citations, while the 99th percentile accrues over 1,080; these figures are similar to those reported by Akcigit et al. (2016). Highly skilled inventors, or 'Stars', are the most productive and important creators in their respective fields, and can shift both local and national investment policies (Zucker et al. (1998)). This makes the consequences of regulatory burden within this subgroup of particular importance, and motivates their study.

In the second part of the paper, I study the impact of regulatory burden on the quantity and quality of inventor output. Inventor output is a function of the inventor's skills, their time spent innovating, and the resources at their disposal. Consequently, I first examine patent quantity, testing the Disruption Hypothesis. According to this hypothesis, if compliance burden decreases the time an inventor can commit to developing innovative ideas, then patent output should decline. Stars have significantly higher marginal productivity of labor than their Non-Star peers, and so it follows that Stars should experience greater disruption and steeper declines in output for the same increase in burden. It is unlikely that inventors would increase their hours worked to fully offset the loss in output.

I regress the count of patents produced by an inventor in a given year on regulatory bur-

3. Given the supervised nature of the aggregation, I report robustness analyses varying each of the idiosyncratic choices in the Internet Appendix. I find consistent results across all aggregations.

den, standard controls from literature, and granular fixed effects. This test yields results consistent with the Disruption Hypothesis: regulatory burden is associated with a reduction in patent output. The effect is economically meaningful; a 1 standard deviation increase in Time Burden decreases inventor-level patent counts by 2%. This reduction is driven by Star Inventors (defined as those above the 95th percentile of productivity over the preceding decade[4] (Moretti and Wilson (2017)), whose output falls by 13.9%. This decline is equivalent, in aggregate, to approximately 14,900 patents annually, or, using the latest Kogan et al. (2017) values converted to 2023 dollar terms, to a loss of about $498B dollars in patent value.[5] I attribute these reductions in labor productivity to compliance consuming more inventor time.

I identify these effects within inventor over time, net of employer-city trends, removing omitted variables like an inventor's broad technological specialization, the employer's time-varying innovation strategy, and the time-varying concentration of innovative activities in a given location. My specification effectively compares two inventors who work in the same employer's establishment at the same time, but have differing levels of burden due to the nature of their innovative activities. Despite the stringency of this test, a potential concern remains that the results are driven by inventors working in mature technology classes. These areas might have extensive regulatory regimes and fewer growth opportunities, and those opportunities may be more incremental in nature. The following robustness analyses address this concern.

First, I assign inventors to a "primary" technology class, based on the class in which they historically patent most often and include Technology Class-by-Year fixed effects. This specification compares inventors who work on similar technologies, but patent in slightly different areas. In this test, I find similar productivity declines on average, and steeper declines among Stars. Second, I separately analyze inventors working in Rapidly Evolving Technology Classes

4. While the 95th percentile of productivity is common in prior literature, I show my results are not sensitive to this choice in robustness analyses. I redefine 'Star' using other productivity thresholds as well as definitions based on citation accumulation, and find results consistent with my primary definition.

5. There are, on average, 24,644 Star Inventors each year with an average annual productivity of 4.376. 24,644 x 4.376 x 0.139 = 14,990 patents. Star-authored patents are worth on average (median) 10.50M (3.22M) in 1982 dollars, and the relevant CPI inflator between January 1982 and January 2023 is 3.17. So, 14,990 x 10.50M x 3.17 = 498B. These figures assume that patents from non-U.S. publicly traded companies (e.g. private firms and foreign firms) are of similar value to U.S. publicly traded company patents, as Kogan et al. (2017) derive values from U.S. stock returns.

and Mature Technology Classes using the Bowen et al. (2022) measure of 'RETech', which classifies technologies as those that displace prior work. I find results consistent with my baseline specifications in each technology class grouping. Patenting practices within technology fields have changed over time, with areas like computer science and chemistry expanding rapidly since the 1990s (Lerner and Seru (2021)). Therefore, in a third robustness test, I exclude inventors working in these technology classes, and find no evidence that my results are driven by field-specific changes in patenting practices. I also show that my results are not driven by the definition of Star Inventor, by inventors residing in California and Massachusetts (Lerner and Seru (2021)), or by small private companies.

In the third part of the paper, I study how regulatory burden changes the type of projects innovators pursue. Given that inventors complete fewer innovations, the selection of which projects to undertake likely shifts. As regulatory burden rises, inventors may prioritize their riskiest projects, or those most likely to be breakthroughs. They might do so because these inventions are the most valuable to the firm, to their careers, and to science more broadly. This Risky Innovation Hypothesis predicts an increase in the overall citation count of innovations, and the creation of more exploratory and original technologies. Alternatively, inventors may instead respond by prioritizing projects with greater certainty or lower variance, developing more incremental or process-oriented innovations. This Strategic Innovation Hypothesis therefore predicts fewer citations overall, fewer citations per patent, and narrower characterization metrics.

To assess these alternatives, I first study citation and text-based measures of patent quality. I find that inventors produce lower quality patents as burden increases, measured either by the number of citations received by completed patents or by the number of novel terms introduced to the patent corpus. Both measures are strongly correlated with highly influential patents and intellectual contributions (Hall et al. (2005), Arts et al. (2021)). Comparing the patents of Stars and Non-Stars, the total quality declines are again concentrated in Stars. A 1 standard deviation increase in Time Burden decreases scaled citations created in a year by 2.8%, conditional on producing a patent. Stars' scaled citations per patent remain unchanged. For the same increase in burden, I find that Stars reduce new terms introduced by 3.1% and

those terms are used 3.5% less by subsequently filed patents. Combined, my results show that Star Inventors decrease the number of patents they produce, and the overall quality of their inventions declines. It appears that inventors narrow the scope of their projects and seek lower risk discoveries, in response to increased burden.

To further characterize the changes in inventor output, I examine measures of novelty (Bowen et al. (2022)), defensiveness (Akcigit and Ates (2019)), and process-orientation (Bena et al. (2022)), constructed from the text, citations, and claims of patents. I find that regulatory burden decreases the 'breakthrough value' of inventor output, consistent with the decline in citations and novel words. I find no evidence that this pattern is driven by increased process patenting or by efforts to build denser patent thickets. This evidence supports the notion that regulatory burden slows the innovation production process, but does not necessarily shift individual inventors' patenting strategies.

Finally, I examine whether regulatory burden distorts the market for high skilled labor. Using detailed public data from the USPTO and Patentsview on the location and assignee of patent inventors, I track individual inventors across their careers, identifying each inventor's employer and residence over time. The Disutility Hypothesis predicts that inventors dislike compliance paperwork. Therefore, increases in regulatory burden will be associated with increased inventor turnover. Under this possibility, inventors with greater market power (Stars) should be most likely to change jobs. It relies on the assumption that burden is more easily changed across employers than within. Alternatively, the Human Capital Hypothesis predicts that inventors may gain importance within their team for efficiently dealing with regulators. Inventors who develop these regulatory skills (Non-Stars) should be less likely to change jobs.

To evaluate the Disutility and Human Capital Hypotheses, I regress an indicator for an inventor changing employers on regulatory burden. I find that a 1 standard deviation increase in Time Burden is associated with a 0.2pp increase in the likelihood of inventor turnover, a 2% increase relative to the unconditional probability of 10pp. The effect is similar for Stars and Non-Stars. I also examine where inventors move, and find evidence that burden increases the likelihood of inventors moving to larger firms, though this tendency is stronger for Non-Stars. I find no support for the Human Capital Hypothesis.

My paper contributes to the literature on how regulation affects innovation. Prior work shows that national political regime and the broad uncertainty around regime change can negatively affect R&D spending and patenting at the country and country-industry-level (Bhattacharya et al. (2017), Pertuze et al. (2019)). Specific policy proposals, e.g. de-burdening small firms of a subset of laws, may benefit those targeted, by allowing the reallocation of funds from auditors, pensions, and labor boards to R&D Spending, which leads to increased patenting (Aghion et al. (2023), Dambra and Gustafson (2021), Prieger (2002)). Recent work reports that inventors affiliated with the political party in power experience increased productivity, buoyed by sentiment, rather than as a result of industry favoritism (Engelberg et al. (2023)). I advance this literature by studying the narrowest unit of innovator, the inventor, and employing the full breadth of federal compliance regulations in the United States. I show that increased time spent on regulatory burden decreases patenting output at the individual-level, and that this decline is concentrated in the most prolific inventors. Moreover, the patents actually completed are of lower quality and narrower scope, providing further evidence of regulatory burden harming inventor careers.

This evidence also grows our understanding of how regulated entities internalize compliance costs. Compliance burden increases many direct costs of regulatory engagements, like SG&A expense and lobbying expense amongst public firms (Kalmenovitz (2023)), and expenditures on compliance-related professionals (Trebbi et al. (2023)). I document that an indirect cost of this regulatory compliance is reducing the productivity of a firm's high skilled labor, as the burden of compliance to inventors is not fully offset by the firm's increased administrative expenditures.

My paper also contributes to the extensive literature on inventor mobility. Disruptive events like bankruptcies (Baghai et al. (2019), Baghai et al. (2021)), mergers (Li and Wang (2023), Cunningham et al. (2021)), hedge fund activism (Brav et al. (2018)), credit shocks (Hombert and Matray (2017)), and terrorist attacks (Fich et al. (2023)), as well as micro-events like taxation (Akcigit et al. (2016), Moretti and Wilson (2017)), and non-compete agreements (Marx et al. (2009)), among others, spur inventor mobility. I add to this literature by showing that inventors move to new jobs to escape the government's compliance burden. This aver-

sion to paperwork even affects Star Inventors, who individually produce the most innovation and raise the productivity of Non-Star coworkers (Zacchia (2018)). Thus, I document a factor firms must consider in their efforts to retain top talent and maximize productivity.

Finally, I contribute to the literature on government regulation and machine learning. The Code of Federal Regulation contains granular information on how administrative agencies restrict activities (Al-Ubaydli and McLaughlin (2017)) and interact with firms (Kalmenovitz (2023), Kalmenovitz et al. (2023), Chen and Kalmenovitz (2023)). Researchers have also developed alternative regulatory measures based on the text of earnings calls (Calomiris et al. (2020)), firm 10-Ks (Kalmenovitz (2023)), and other corporate disclosures. My own measures, based on patent text, enable the study of how administrative agencies regulate innovative firms and their inventors. I provide evidence that these regulations are costly to patenting efforts, decreasing both output and efficiency. These results inform how regulators must consider rulemaking not just in isolation, but in terms of how the marginal rule contributes to specific workers' overall level of burden.

2 Background

In this section, I first describe how the federal government generates paperwork regulations and their associated burden estimates. I then review the literature on star scientists and discuss how this group differs from their 'non-star' peers. I conclude with an overview of the inventor production process.

2.1 Paperwork Regulations

The Paperwork Reduction Act (PRA), first passed in 1980, created the Office of Information and Regulatory Affairs (OIRA), a sub-agency of the Office of Management and Budget (OMB). OIRA governs how federal regulators collect information from the public, standardizing the process of developing and approving paperwork regulations. It also provides extensive guidance on how to estimate a regulation's burden. These regulations enforce 'good behavior' among market participants through reporting requirements, and address broad government

concerns, like protecting consumer welfare and maintaining competitive markets.

Once an agency decides a PRA-applicable information collection is necessary, an independent team within the same agency analyzes the intended collection. This analysis reviews the collection's purpose, scope, and intended respondents, and then applies uniform guidelines from OIRA to develop a public proposal. The proposal is then posted to the Federal Register website for a 60-day public comment period, where individuals, firms, lobbyists, and other parties may provide feedback. After reviewing public comments and concluding its internal review, the agency then submits a more detailed package to the OMB, describing the initial collection proposal, the public comments, and how the agency updated the proposal to reflect these comments. Upon submission, the agency must post the updated document and notice of the OMB submission to the Federal Register website, and allow 30 days for public comment. The OMB will incorporate any additional public comments in its decision whether to approve the regulation with or without changes, and changes may include increasing the estimated burden (or simplifying the collection so as to decrease burden on respondents). The agency must repeat this entire process when seeking to renew or revise a collection. OIRA estimates this process requires 6-9 months per regulation at minimum.

After the final approval, a Form 83-I is posted to the OIRA website, which records details of the regulation and the final burden estimates. Burden is reported in terms of time per response, number of responses required per year, and the dollar cost of that response. The time estimates include the time needed to train workers on the collection, and the actual information collection and reporting to relevant agencies. The dollar costs include the hiring of third parties, one-off capital investments, and the wages of respondents. Agencies are encouraged to use Bureau of Labor Statistics for wage data. These estimates are not only reviewed by the agency initiating the collecting and the regulated parties (e.g. firms), but also by the Government Accountability Office (GAO). The GAO is an independent, non-partisan agency tasked with improving the efficiency of government activities and saving taxpayer money. The many independent parties involved in the process of burden estimation, each with varied motivations, mitigates concerns about burden being incorrect or biased.

2.2 Star Inventors

The most prolific and important inventors are often referred to in the literature as 'Stars' or 'superstars', as they create the largest number of patents and accrue the most citations. Star Inventors also improve the quality of their peers' work and facilitate knowledge diffusion within firm (Zacchia (2018)). Using individual wage data from the U.S. Census Bureau, Akcigit and Goldschlag (2023) show that 88% of Stars in their sample earn wages in the top decile of the income distribution, and 19% earn wages in the top percentile. Due to their intrinsic value to innovative efforts, Star Inventors are highly mobile, across both geography and employers; Moretti and Wilson (2017) report that Star Scientists in 2006 are nearly 3x as mobile as the average American with a graduate degree. This ease of mobility allows them to be quite sensitive to environmental factors, like personal income tax rates (Akcigit et al. (2016), Moretti and Wilson (2017)) and firm-level financial factors (Baghai et al. (2021)), Hombert and Matray (2017)), and demonstrate how Stars leverage their importance to improve their working conditions.

On a macroeconomic scale, Stars' migratory decisions have large consequences for their industries and countries. New firm entry and incumbent firm investment follow Star movements, both within and across countries, independent of Stars' ex ante inventions in a given location (Zucker et al. (1998), Zucker and Darby (2014), Akcigit et al. (2016)). In this context, Stars' decisions about where to live, whom to work for, and what technologies to develop are highly influential. These real effects, are attributed to their specific human capital, and motivate why their time is worth studying.

2.3 Innovation Production Process

Individual patent production can be considered a function of the inventor's skill, the units of their time they apply to producing patents, and the resources at their disposal. The distribution of inventor skill, at least as measured by inventor citations, is significantly skewed. The median inventor in my sample accumulated 14 citations between 1993 to 2020, while the 99^{th} percentile accrued over 1,080 citations. These figures are quite similar to those in the Akcigit

et al. (2016) global sample following inventors productive between 1977 and 2000. A natural interpretation of these statistics is that inventors of higher skill are more productive for the same units of time and resources allocated to innovation.

When inventors commit time to producing innovation, that time is spent creating ideas, developing their implementation, and producing the final patent. Regulatory burden primarily affects the intermediate phase of implementing ideas, lengthening the overall time from idea conception to project completion. Thus, the time necessary for an inventor to create a given level of output is the time to complete the actual idea, plus the time to deal with regulatory hurdles. It follows that inventors would be more productive in a world without regulation, as all their time could be allocated to developing and implementing ideas.

If compliance burden detracts from hours spent innovating, then the more skilled inventors should see the largest reductions in their output. The higher an inventor's marginal productivity, the greater the output lost from reducing time committed to innovation. Under this conjecture, inventors will not increase their total hours spent working to fully offset the productivity lost to regulatory compliance. Instead, an increase in burden leads to an overall reduction in output, with inventors in equilibrium positively adjusting their total hours worked according to their skill level.

3 Hypothesis Development

3.1 Patent Quantity Hypothesis

As discussed previously, patents at the individual level are a function of inventor time, skills, and resources. Increases in compliance paperwork should detract from the time an inventor can spend developing new ideas. However, it is possible that regulation has no discernible impact on individual-level patenting, since innovators may partially *delegate* those tasks to compliance specialists within the firm. Reading regulations casts doubt on this possibility, as some regulations require detailed disclosures about the innovations known only to experts. Additionally, paperwork regulations are as much about conduct as filling out forms, and so they may be viewed as a proxy for other related regulations. For example, clinical drug trials

must report on the quality management system deployed (pre-trial), any adverse reactions (as they occur), and certify the final results (post-trial). The nature of these responses makes fully outsourcing the burden to a compliance department or regulatory specialist difficult. However, this compliance paperwork also discourages 'cutting corners' ex ante, as disclosure may prompt investigations for violating other regulations.

The Disruption Hypothesis predicts that regulatory burden constrains innovators' technological progress by increasing the amount of time they spend per completed patent, decreasing the number of patents completed. While governments often invest significant resources into innovation initiatives (e.g., 2023 CHIPS Act, NASA), agencies typically prioritize consumer and worker safety (e.g., FDA, FAA), firm competition (e.g., FTC), and limiting negative externalities (e.g., EPA). To satisfy these competing priorities, agencies require disclosure of information about firm activities and evidence of compliance. As the costs (e.g., time) of these disclosures increase, the quantity of innovation output declines.

Stars should experience steeper declines in productivity for the same increase in regulatory burden. Given similarly finite time to invent, a Star produces far more output than a Non-Star. A reduction in this time produces a larger negative response in Stars, as they have significantly higher marginal productivity of labor.

3.2 Innovation Quality Hypotheses

Regulatory burden may also affect the quality and type of patents completed. As inventor time is constrained, we would expect the projects undertaken to shift in composition.

The Risky Exploration Hypothesis suggests that inventors may prioritize their riskiest projects, or those most likely to be 'breakthroughs', as regulatory burden rises. Firms reward employees for developing breakthrough technologies through raises and profit-sharing plans, and these financial incentives are commonly used to motivate Stars (Akcigit et al. (2016), Akcigit and Goldschlag (2023)). Inventors may subsequently increase their efforts on these high risk, high reward projects, and decrease time spent on their more certain, but lower reward, projects. This hypothesis predicts that completed innovations will be higher quality (more citations), more original, and more likely to be breakthroughs. It may also be the case

that these patterns differ across inventor type (Star vs Non-Star), with Stars more likely to prioritize their riskier projects, given their stronger financial and reputational concerns.

On the other hand, the Strategic Innovation Hypothesis predicts that regulatory burden may incentivize inventors toward more conservative, strategic, or process-oriented projects. As regulatory burden rises, SG&A expense, cost of goods sold, and lobbying expenditures, all increase (Kalmenovitz (2023)). Inventors and firms may prioritize process patents, which improve efficiency, lower production costs, and build primarily on existing firm knowledge (Bena et al. (2022)). It would be reasonable to expect decreased citations (total and per patent) and increased process-orientation, as inventors produce patents of a narrower, more incremental nature.

3.3 Labor Mobility Hypotheses

I track individual inventors across their careers, identifying each inventor's employer and location over time. I record transitions between employers as one measure of labor mobility. The Disutility Hypothesis predicts that inventors dislike compliance paperwork. Therefore, increases in regulatory burden should be associated with increased inventor turnover. This assumes that workers can more easily adjust their burden or projects by moving externally (as opposed to internally). Moreover, inventors with greater market power (Stars) should be more likely to change jobs, as they are more sensitive to negative factors (Akcigit et al. (2016), Moretti and Wilson (2017)). These 'movers' should seek less burdened positions, either due to earlier stage projects or altogether different areas.

Alternatively, the Human Capital Hypothesis predicts that inventors may gain importance within their team for efficiently dealing with regulatory compliance. Specialization in compliance regulations may lead to increased job security or inclusion on additional inventor teams. The hypothesis predicts that inventors who develop regulatory skills should then be less likely to change jobs, and that Non-Stars have the highest incentive to take on these types of roles, given Stars' comparative advantage in patenting.

4 Research Design

4.1 Examining Patent Quantity and Quality

Many innovation outcomes exhibit significant positive skew and large mass at zero. Hall et al. (2005) report that 25% of patents in their sample received zero citations; 28% of the patents used in this paper have zero citations. Cohn et al. (2022) show that count, count-like, and rate outcomes with significant mass at zero are best modeled using Poisson Pseudo-Maximum Likelihood. Including higher dimensional fixed effects in this procedure has become computationally feasible due to the algorithm developed by Correia et al. (2020; 2021). Thus, in all count(-like) outcome variable analyses, I use Poisson Pseudo-Maximum Likelihood with fixed effects of varying stringency and time-varying inventor-level controls, specifically:

$$log(\mathbb{E}[y_{i,j,l,t}|\mathbf{X}]) = \beta_1 \text{Time Burden}_{i,t-1} + \beta \mathbf{X}_{i,t-1} + \alpha_i + \alpha_{j,l,t}$$

where i represents inventor, j represents employer, l represents city, and t represents year. $y_{i,j,l,t}$ contains outcomes like patents produced in a year, citations earned by patents filed, and new words introduced to patent corpus by patents filed. All independent variables are lagged by 1 year to reduce concerns of reverse causality.

I construct common controls from prior literature (Hombert and Matray (2017), Marx et al. (2009), Akcigit et al. (2016)). I include an inventor's patenting experience, defined as the number of years since her first patent filing (logged) to control for career progression. I also include their productivity over the preceding 5 years (logged) to account for recent activity and market value; I exclude this from patent output specifications, as it is a function of the lagged dependent variable. I include number of years since the inventor's most recent patent (logged) to account for differing patent practices across technology areas. Lastly, I include an indicator for whether the inventor is individually assigned a patent in a given year, representing either "side-hustle inventing" or greater leverage within the primary assignee.

For binary and continuous measures of inventor characterization, I will use the following

linear specification:

$$\mathbb{E}[y_{i,j,l,t}|\mathbf{X}] = \beta_1 \text{Time Burden}_{i,t-1} + \beta \mathbf{X}_{i,t-1} + \alpha_i + \alpha_{j,l,t}$$

where the subscripts, fixed effects, and controls are the same as above. $y_{i,j,l,t}$ contains outcomes like generality, originality, and an indicator for whether an inventor created a process patent in a year, among others.

Standard errors in all specifications are clustered at the inventor and assignee-level, as the variation in Time Burden occurs at the inventor-year level and there may be correlations between inventor clusters within the same assignee (Petersen (2008)).[6] All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles within Star grouping.

I include inventor fixed effects to control for time-invariant inventor-level characteristics, like gender, race, education, ability, and initial wealth. Controlling for these characteristics facilitates determining the differential impacts on Star vs Non-Star inventors. I define "Star" as an inventor in the 95^{th} percentile of patent production over the previous decade (Moretti and Wilson (2017)). To show my results are not sensitive to this choice, I report results using other productivity thresholds, and definitions based on citations, for "Star" in Table 10.

I then report results net of time-invariant employer characteristics and macroeconomic trends (assignee and year FE), net of employer trends (assignee-by-year FE), and net of time-invariant city characteristics. In my most stringent specification, I include employer-by-city-by-year fixed effects to compare inventors working for one firm at the same time and in the same city, but with different levels of innovation-specific burden. This mitigates concerns about geographically dispersed "mega-firms" (Braguinsky et al. (2023)) and high tech clusters (Moretti (2021)). It also absorbs factors like time-varying employer innovation strategy and the geographic concentration of specific innovation activities in certain establishments.

A concern remains that β_1 may capture how the maturity of a technology area affects patent quantity and quality, rather than the regulatory burden itself. Older innovation areas with more mature and potentially more burdensome regulatory regimes may have fewer

6. In Table 13, I report alternative clustering, to address concerns about correlations between inventor clusters within the same assignee-year, and one-way clustering at the inventor-level, though clustering at the inventor and assignee-level is the most conservative (theoretically and empirically).

growth opportunities, and those opportunities may also be more incremental in nature. While average technological maturity during an inventor's career is absorbed by inventor fixed effects, and increases in maturity are partially absorbed by employer-by-year fixed effects, I employ multiple robustness tests in Section 7.1 to directly address this concern.

4.2 Examining Mobility

To examine inventor transitions between and within firms, I use a linear specification with high dimensional fixed effects and controls as above:

$$\mathbb{E}[\mathbb{1}(\text{Change Jobs})_{i,j,l,t}|\mathbf{X}] = \beta_1 \text{Time Burden}_{i,t-1} + \beta \mathbf{X}_{i,t-1} + \alpha_i + \alpha_{j,l,t}$$

where i represents inventor, j represents employer, l represents city, and t represents year. $\mathbb{1}(\text{Change Jobs})$ is an indicator for an inventor moving to a new employer. In additional analyses, I will replace $\mathbb{1}(\text{Change Jobs})$ with an indicator for moving locations within the firm, and indicators for moving to different types of firms.

5 Data

In this section, I discuss the data used in the empirical analysis. First, I describe the procedure and methods used to estimate an inventor's regulatory burden. Second, I detail the construction of the inventor panel dataset. Third, I discuss the proxies used to measure the quality and characterization of inventors' completed innovations. Internet Appendix Table A1 contains details of variable construction.

5.1 Inventor-level Burden Estimation

I begin with the text of all active paperwork regulations during the period 1993 to 2020.[7] To represent the regulation, I concatenate its title, the issuing agency's name, and the description of the collection discussing its scope and purpose. Prior literature uses various methods

7. I thank Joseph Kalmenovitz for sharing these texts (Form 83-I) scraped from the Office of Information and Regulatory Affairs (OIRA). "Regulation" refers to unique OMB Control Numbers.

to explore regulations, like counts of "restrictive words" (George Mason University Mercatus Center Regdata, Al-Ubaydli and McLaughlin (2017)), complexity measures (Amadxarif et al. (2019); Colliard and Georg (2023)); de Lucio and Mora-Sanguinetti (2022)), firm-level intensity (Kalmenovitz (2023)), firm-level fragmentation (Kalmenovitz et al. (2023)), among others. There are more than 25,000 federal paperwork regulations in my sample, from 96 agencies and 261 sub-agencies. I apply standard pre-processing steps to this regulatory corpus, such as converting to lowercase and removing stopwords, punctuation, and numbers. I do not stem or lemmatize words, as this often impairs topic modeling quality (Schofield and Mimno (2016)).

Regulations have considerable heterogeneity in scope, with some spanning many activities and others having quite narrow focus. To best capture this variation, I use structural topic modeling (STM) (Roberts et al. (2019)) to identify topics in the text of these regulations. STM is similar to latent dirichlet allocation (LDA); it is an unsupervised machine learning method which produces a topic distribution for given k topics for each document (regulation), where a topic is a "cluster of co-occurring words" (Blei et al. (2003)). The key difference is that STM can use covariates to inform topic assignment, incorporating information 'learned' from, e.g., one FDA regulation to another. I include as topic prevalance covariates the Agency (e.g., Department of Health and Human Services), Sub-Agency (e.g., Food and Drug Administration), and implementation year of the regulation.

STM is a form of unsupervised machine learning, where the only user-supplied input is the number of topics k. I supply k between 60 and 300, as 60 is the recommended lower bound for a corpus of this size (Roberts et al. (2019)). For each model, I implement the default "Spectral Initialization" estimation procedure, as this is considered best practice (S. Arora et al. (2013), Roberts et al. (2016)) and yields identical results regardless of the initial seed value. Figure 1 reports diagnostics on these models, and I use visual inspection to select 150 topics, as it minimizes residual dispersion (Grimmer and Stewart (2013)). Kalmenovitz et al. (2023) use LDA to identify 100 topics in their corpus of federal notices and proposals, and Dyer et al. (2017) use LDA to identify 150 topics in 10-K filings. The topics are also semantically coherent, in that words grouped together are, upon inspection, thematically similar (Mimno et al. (2011). Figure 2 reports word clouds for several topics.

I then fit this regulation-trained model to patent text, concatenating a patent's title, abstract, and claims to represent the patent, as in Arts et al. (2021). There are over 5 million utility patents in my sample, filed from domestic and foreign applicants. This model fitting yields a topic distribution for each patent, i.e., Patent A is X% Topic 1, Y% Topic 2, and so on. This distribution measures the degree of overlap between the language used in patents and the language of each topic. To minimize the impact of "general/common" topics and to reduce noise, I residualize the patent topic distributions. This emphasizes the topics which have a high overlap with specific patents and de-emphasizes topics which overlap with many patents. I also set to zero all topics comprising less than 1% of a patent, as none of the estimated topic proportions are exactly zero.[8] Broadly, this procedure relies on regulators and patents using a common language to describe what is important, similar to the assumptions in the earnings call literature about CEOs and analysts discussing topics of mutual importance.

To estimate a patent-level burden, I first compute the burden associated with a topic over time. I assign burden to topics as the sum-product of the estimated topic distributions for each regulation and that regulation's burden estimates from its Form 83-I at time t, such that:

$$\text{Topic Burden}_{k,t} = \sum_{r} (\theta_{k,r} \cdot \text{Regulation Burden}_{r,t})$$

where $\theta_{k,r}$ represents the topic proportion of a given regulation, k represents topic, r represents regulation, and t is year. I then compute a patent's burden similarly, as the sum-product of that patent's estimated topic proportions and the burden of each topic in the patent's filing year:

$$\text{Patent Burden}_{p,f} = \sum_{k} (\theta_{k,p} \cdot \text{Topic Burden}_{k,f})$$

where $\theta_{k,p}$ represents the topic proportion of a patent, k represents topic, p represents patent, and f is the year of the patent's filing, as this is considered the best proxy for when the innovation was actually created (Griliches et al. (1986)).

I examine burden for different technology classes in Figure 3, by plotting the average

8. The patent burden used in primary analyses is $\geq$90% correlated with patent burden estimates using unresidualized topic distributions, and setting to zero any topics with less than 1% or 5% overlap without residualizing. Correlations are reported in Internet Appendix Table A2.

Time Burden for each of the Cooperative Patent Classification's (CPC) broadest technology classification groupings (CPC Section). This classification schema is jointly developed by the USPTO and the European Patent Office (EPO). The time trend in compliance burden is consistent across all types of innovation, though the relative positioning of CPC Sections changes over time. The highest burden CPC Section, "Physics," contains innovations related to nuclear engineering, computers, and information technology. The lowest burden CPC Section, "Chemistry; Metallurgy," contains additives for consumer products (e.g., paints, dyes, resins), microorganisms used in the production of fermented products (e.g., beer), and chemical processes used in the manufacture of metals.

Using these patent-level burdens directly for an inventor's burden is problematic. Patent burdens are cross-sections in time, and inventors may have gaps between their productive years. During those 'gaps', new regulations are created and old ones are sunsetted, meaning that regulatory burden for certain types of projects will change. These changes would not be captured by an interpolation or simple 'carrying forward' of most recent burden. However, technology classes have patent filings each year, and this information allows assignment of updated burden to inventors, even when those inventors are not productive. It also mitigates any given patent burden's noise, by aggregating filings together. I use CPC Class (e.g., C07), as it is considerably more granular than CPC Section.

To calculate an inventor's individual burden, I determine the relevant CPC Classes that the inventor works on throughout her career by noting when an inventor files in a patent class. I consider a Class to be irrelevant if an inventor has not published in it for 4 years; this choice is motivated by the (growing) average number of years between patent file and grant date, plus development time of the innovation itself. I then aggregate the patent burdens to the patent's technology class by using the median burden of patents filed in that class in a year, to construct a class's burden over time.

$$\text{CPC Class Burden}_{c,f} = \text{Mdn}\{\text{Patent Burden}_{p,f}\}_{c,f}$$

where c represents CPC Class and $\text{Mdn}\{\}_{c,f}$ refers to the median of the patent set filed in class c in filing year f. I then calculate the median of an inventor's relevant technology classes to

estimate their burden:

$$\text{Inventor Burden}_{i,t} = \text{Mdn}\{\text{CPC Class Burden}_{c,f}\}_{i,c,t}$$

where i represents inventor and $\text{Mdn}\{\}_{i,c,t}$ refers to the median of an inventor's relevant classes at time t. Using the median to represent burden mitigates concerns of outlier patents (patent classes) unduly influencing the final estimate. This procedure yields two measures, Time Burden and Paperwork Burden.[9]

As an initial validation of my measures, I report correlations between other text-based regulatory burden measures, namely the (public) firm-level measures from Kalmenovitz (2023) and the annual measures from Al-Ubaydli and McLaughlin (2017) in Table 1. All measures are moderately positively correlated. "Time Burden" and "Paperwork Burden" are positively correlated, though less so than "Time Burden" is with other regulatory burden measures. This suggests the two measures identify different aspects of the administrative state, such as frequency and intensity of engagement. I also perform a variance decomposition in Table A5, regressing Time Burden on various fixed effects and reporting the R^2. Time-invariant employer characteristics (employer FE) account for 36.1% of the variation in Time Burden, and time-varying employer characteristics account for a further 31.4%. Thus, 32.5% of the variation occurs at the inventor level. This can be separated into a time-invariant component (inventor FE) of 20.5% and a time-varying component of 12%.

As my focus is innovation, I hypothesize that Time Burden will be particularly salient to inventors. Multiple regulations may be satisfied by a single, short engagement with regulators. However, "hours" should better proxy for the potential burden on inventors, as their knowledge work has a high marginal product of labor. Kalmenovitz (2023) reports that the fraction of US working hours comprised of regulatory compliance rose from about 2.5% in 1990 to about 4% in 2020, and that in 2020, over 10 billion working hours were spent by company employees complying with regulatory burden. Therefore, Time Burden is not just economi-

9. Inventor-level estimates using the average of patent and class burdens instead of median, or holding classes relevant for fewer than 4 years, or using CPC Sub-class instead of Class are $\geq$78% correlated with the measures used in this paper. Correlations are reported in Internet Appendix Table A3. Results using these alternative measures are reported in Internet Appendix Table A4.

cally meaningful from a theoretical perspective, but is also a significant portion of American job responsibilities.

5.2 Inventor Time Series Construction

I begin with all inventors associated with utility patents in the USPTO-Patentsview database, and their associated location and assignee data. The primary advantage of this database is its disambiguation algorithm, which produces unique identifiers for inventors, assignees, and locations; raw patent data from the USPTO is entirely unstandardized.

Because inventors are only observed when they produce patents, I create a time series by imputing between an inventor's filed (and subsequently granted) patents. I first omit one-time patent grantees, as they cannot enter estimation. For the remaining inventors with at least 2 patents, I assign the inventors' presumed employers (the assignee of their patents) and known residence locations using a midpoint assumption for the intervening years (Akcigit et al. (2016), Marx et al. (2009), Hombert and Matray (2017)). Inventors are required to list their primary residence on patent applications, and have no reason to misrepresent this information, as it does not have any bearing on their taxes, profit-sharing, or credit for the innovation. To match inventors to employers, I check that inventors frequently file with that assignee, both within a given year and historically. I omit inventors for whom I cannot assign an employer with confidence, e.g., they file for two different employers every year with the same quantity of patents. If an inventor is observed at employer A in year t and employer B in year $s > t$, then I assume she works for A until $t + (s - t)/2$, and for B until s (inclusive). If an inventor only produces 1 patent, but continues to work for the employer, I cannot observe those later "unproductive" years or create a time series for this inventor. Similarly, I cannot observe an inventor who works for 1 firm and moves to another, but never produces a patent for the second firm. This assumption leads to a conservative estimate of both movement and years within sample, meaning that there are likely additional years of zero patents both before and after my times series for certain inventors.

I use the A. Arora et al. (2021) (DISCERN) and Ewens and Marx (2023) linktables to categorize inventors as working for U.S. publicly traded firms, private firms, and universities. Patent

applications also require filers to classify themselves as a domestic or foreign organization, domestic or foreign government, or an individual. For those inventors who only report individual assignee type (or always have a missing assignee), I assign the label "Self-Employed." For those inventors who also have individually assigned patents while primarily working for corporate or government assignees, I construct the control variable "Individual Assignee," to indicate either "side-hustle inventing" or greater leverage within the primary employer.

I keep records between 1993 and 2020, retaining all patents applied for and granted by the US Patent and Trademark Office (USPTO). The sample ends in 2020, because patents take about 2-3 years to be granted, so this eliminates years with the most severe truncation bias in patent counts (Hall et al. (2001), Lerner and Seru (2021)). My final sample contains 1.4 million inventors, 12.6 million inventor-years, and 216,000 employers.[10] In the main text, I define "Star" as an inventor in the 95^{th} percentile of patent production over the previous decade (similarly to Moretti and Wilson (2014), Moretti and Wilson (2017), Akcigit et al. (2016)), with alternative definitions explored in robustness. Summary statistics are reported in Table 2. Inventors change assignees in about 10% of inventor years, comparable to (Hombert and Matray (2017), Marx et al. (2009)).

5.3 Patent Quality and Characterization Proxies

I use two proxies for the quality of an inventor's creations: patent citations and the count of new words introduced to the patent corpus. Citations are the original measure of patent quality, and higher citation counts demonstrate significant monetary and scientific value (Trajtenberg (1990), Hall et al. (2005), Kogan et al. (2017)). However, existing literature has identified some shortcomings of citations, like strategic citing (Lampe (2012)), patent examiner busyness and expertise (Righi and Simcoe (2019), Lei and Wright (2017)), and changing citation practices (Kuhn et al. (2020)). To circumvent these issues, I use data shared publicly by Arts et al. (2021) to examine the new words introduced by a patent to the patent corpus, and their subsequent reuse. Patents that use new words (in the patent corpus) for the first

10. Estimation samples are smaller as singletons and observations separated by fixed effects are omitted. Inclusion would lead to biased standard errors and inference when fixed effects are nested within clusters (Correia et al. (2020), Correia (2015)).

time are positively associated with prestigious innovation awards, like Nobel Prizes and Turing Awards. Thus, higher numbers of newly introduced words represent higher novelty and scientific contribution (Arts et al. (2021)).

First, I construct common citation measures, including citation count, generality, and originality. Raw citations suffer truncation bias similarly to the count of patents, in that patents filed later in the sample have fewer years to accrue citations, and there are large differences in citation practices across technology area. Following Hall et al. (2001) and Lerner and Seru (2021), I first divide a patent's raw citation count by the average number of citations received by patents in the same technology class and filing year as the focal patent. I then aggregate these counts to the inventor-level, as a proxy for the total innovation quality created in a given year, and construct a citations per patent measure as well.

To further evaluate the quality of patents created, I calculate two citation-based measures of patent characterization. Generality uses patent citations to track the range of technology classes a patent influences, and Originality measures how wide a range of technology classes were incorporated into the patent itself (Trajtenburg et al. (1997)). I adjust both of these to account for biases inherent in citations (Jaffe and Trajtenberg (2002), Hall (2005)). I then average these values at the inventor-year level.

Second, I construct analogous text-based measures[11]. In addition to newly introduced words (unigrams), the introduction of new bigrams (e.g., "wireless internet") and trigrams (e.g., "graphic user interface") have similar novel value. Because each of these are important, I examine "New n-grams Introduced" by an inventor in a given year, equal to the sum of new unigrams, bigrams, and trigrams introduced by an inventor's patents in a given year. I also scale this measure by the number of patents produced by an inventor in that year. These measures characterize patents' novelty. For text-based impact, I examine the reuse of these newly introduced n-grams, assuming that greater usage of these newly introduced terms is a mark of those terms' importance to future work (Arts et al. (2021)).

Because these text-based measures likely differ significantly across technology fields, I scale the New n-grams Introduced and New n-grams Reused by the average of patents in that

11. Arts et al. (2021) share publicly the data used to build these text-based measures in a public repository.

technology class and filing year, before aggregating to the inventor-year level. Note that the number of observations is lower because data are made available through May of 2018, and so I use only observations through the end of 2017.

Finally, I construct proxies to characterize the disruptiveness, process-orientation, and defensiveness of inventors' patent output. To measure "breakthrough" innovation, I use the Bowen et al. (2022) data on Rapidly Evolving Technology (RETech) and Technological Breadth (Breadth).[12] Bowen et al. (2022) identify words in patent descriptions that are used with increasing frequency in given technology areas, and demonstrate that patents intensely using these words are at the forefront of technological waves. Intensive use of newly advancing words produces high positive values of RETech, while use of words on the decline produce low or negative values. I calculate the sum of RETech created by an inventor in a year, and RETech per patent. Because RETech is heavily skewed and high RETech patents are quite valuable, I also create an indicator for an inventor creating a patent in the top decile of RETech in a filing year. Lastly, Breadth examines the fields from which a patent draws vocabulary, with higher values indicating broader integration of terminology. I calculate the average Breadth of an inventor's patents in a year.

Assignees often cite their own patents to create thickets and discourage innovating near the nebulous boundaries of their portfolio (Akcigit and Ates (2019)). The self-cite ratio, or the count of a patent's backward citations to other assignee-owned patents divided by total backwards citations, measures how "strategic" or defensive a patent is. Economically, we may expect that as the marginal cost of producing "exploratory" innovation increases, the marginal benefit of protecting already produced innovations may increase. I calculate the average self-cite ratio of patents at the inventor-year level, and, conditional on patenting, evaluate whether inventors shift towards more defensive innovation.[13] I also construct an indicator for an inventor creating a defensive patent(s) in a year, defined as above average self-cite ratio within a patent class and filing year.

If breakthroughs become more difficult to discover, we may also expect assignees to create

12. Donald Bowen's personal website.

13. Note that the number of observations falls because some patents do not cite any utility patents (i.e., they cite only non-patent literature or patent applications) and I omit these from the analysis. Results are robust to their inclusion.

more "process" patents, to improve the efficiency of production processes (Bena et al. (2022)). These patents are highly valuable to their assignee, but traditionally have little external scientific value, as they are internally focused. I use the process claim data shared publicly by Jan Bena to examine process-oriented innovation.[14] I construct two measures from these data: the number of process claims (scaled by technology class and year) per patent and the likelihood of an inventor creating a patent with above average (by class and filing year) process claims in a given year. The former provides a continuous measure of process-orientation (i.e., do inventors identify process improvements in process and non-process patents alike) and the latter allows for an overall shift (i.e., are inventors more likely to produce a process patent as burden increases). Similar measures, e.g., unscaled process claims, more than half of patent claims being 'process' claims, or having more than 1 process claim in a patent, are all quite similar.

6 Results

My primary variable of interest is an estimate of the time an inventor spends complying with paperwork from the U.S. Federal Government. I first examine how regulatory burden is associated with productivity, on average and within Star/Non-Star grouping. I then turn to the quality and characterization of this output. Finally, I analyze the inventor labor market. Robustness analyses follow this section.

6.1 Inventor Productivity

Given finite time to invent, increases in "Time Burden" should detract from time spent generating and implementing new ideas. Further, we may expect a differential impact based on inventor type, Star or Non-Star. In Table 3 Panel A, I examine how regulatory compliance affects individual productivity, using the inventor-level count of patents produced in a year.[15] All continuous independent variables have been standardized for ease of interpretation. Con-

14. Jan Bena's personal website.

15. Coauthor-weighted patents and citation-weighted patents are other common measures of productivity, and I report quantitatively similar results using these alternative dependent variables in Internet Appendix Table A6.

trolling for inventor, employer, and year fixed effects, Time Burden exhibits a negative, statistically significant association with productivity in Column (1); a 1 standard deviation increase in Time Burden is associated with a 1.7% decline in patent output. In Columns (2) and (3), I add additional fixed effects, removing employer trends and time-invariant city characteristics. This exploits variation within inventor over time, and compares inventors working for the same employer in the same year. The coefficient remains statistically significant; a 1 standard deviation increase in Time Burden is associated with a 2.1% decline in patent output.

In my most stringent specification, Columns (4), (5), and (6), I remove employer-by-city trends, comparing the productivity of two inventors working concurrently at the same establishment. In Columns (5) and (6), I also control for inventor-level observables. On average, a 1 standard deviation increase in Time Burden is associated with a 2% reduction in patent output. In Column (6), this is driven by Star Inventors, who experience a 13.9% reduction in patent output. The reduction is equivalent, in aggregate, to approximately 14,990 patents annually, or, using the latest Kogan et al. (2017) values converted to 2023 dollar terms, a loss of about $498B dollars in patent value.[16] Put differently, this is approximately the value of 38,000 statistical lives each year, using the 2023 Department of Health and Human Services estimate ($13.1M). These results quantify the cost to innovation of compliance burden, as well as offer stronger validation of my burden measures.

In Table 3 Panel B, I explore how an inventor's regulatory burden interacts with her location and type of employer, testing the concern that this may be driven by, respectively, foreign inventors and foreign employers. First, I compare inventors living in the United States to those in other countries. About 51% of the sample reside in the United States. Patent applications require that applicants disclose whether they are a domestic (U.S.) institution, foreign institution, or government. I use the Ewens and Marx (2023) linktable to distinguish universities from domestic and foreign entities, meaning that the remaining assignees are generally firms.

16. There are, on average, 24,644 Star Inventors each year with an average annual productivity of 4.376 patents. Exponentiating the coefficient, $1 - e^{-0.15} = 0.139$. So, 24,644 x 4.376 x 0.139 = 14,990 patents. Star-authored patents are worth on average (median) 10.50M (3.22M) in 1982 dollars, and the relevant CPI inflator between January 1982 and January 2023 is 3.17. So, 14,990 x 10.50M x 3.17 = 498B. Using the median value of Star-authored patents yields a loss of $153B. These figures assume that patents from non-U.S. publicly traded companies (e.g. private firms and foreign firms) are of similar value to U.S. publicly traded company patents, as Kogan et al. (2017) derive values from U.S. stock returns.

The correlation coefficient between indicators for "US-based Inventor" and "Domestic Firm" is 0.687.

In Column (1) and (3), I find statistically significant and negative coefficients for both US-based (-1.7%) and Foreign-based Inventors (-2.0%). I find a similar relation between Domestic Firms (-1.9%) and Foreign Firms (-2.1%) in Column (5) and (7), in that I observe a statistically significant and negative coefficient within each group. These results support the view that regulatory burden adversely affects all inventors similarly, regardless of domestic or international location or employment. When splitting inventors into Stars and Non-Stars in the even columns of Panel B, I find similar magnitudes across all categories for Star Inventors; a 1 standard deviation increase in Time Burden is associated with a 12%-15.2% reduction in output. Non-Stars are weakly positively affected by Time Burden, which may be attributable to redistribution of projects from Stars to Non-Stars as burden increases (Zacchia (2018)). These similar coefficients across groupings suggest Foreign-based Inventors and Foreign Firms engage American regulators at a similar frequency to their U.S. counterparts. They are also similarly productive (reported in the table's footer).

6.2 Patent Impact and Characterization

The productivity results suggest that increased burden may change the focus of inventor efforts. As the marginal cost of innovation increases, the quantity falls. If regulatory burden constrains inventor time, inventors may prioritize projects they perceive to be breakthrough inventions, and the quality of completed innovations would thus increase (Risky Innovation Hypothesis). Alternatively, this time constraint could decrease patent quality, and encourage strategic patenting at the expense of breakthrough or exploratory innovations, because the former are considered more incremental than the latter (Strategic Innovation Hypothesis).

6.2.1 Citation-based Measures

To inform these hypotheses, in Table 4 Panel A, I explore how Time Burden affects citations and citations per patent. Patent citations are commonly considered a measure of patent quality; patents with many citations are generally considered more influential. Because patent ex-

aminers (USPTO-employed subject matter experts) add citations to patent applications which assignees may have 'missed,' strategically or inadvertently, patent citations are also considered largely accurate.

I report results using both the raw number of citations, and the number of citations a patent receives scaled by the average number of citations received by a patent in that technology class and filing year (accounting for technological differences and truncation bias (Hall (2005), Jaffe and Trajtenberg (2002))), with scaled citations being preferred (and thus first). I address aggregation concerns raised by Lerner and Seru (2021) by scaling citations at the patent-level, before aggregating to the inventor-level. All columns use Poisson specifications, as all dependent variables exhibit significant positive skew. I only report results net of employer-by-city trends, as these fixed effects absorb factors like an employer's time-varying preference to cite its own patent stock (Akcigit and Ates (2019)) and the localization or visibility effect of patents generated in high inventor concentration areas (Jaffe et al. (1993)).

In Column (1), increased Time Burden is significantly and negatively related to total scaled citations. This result provides evidence that combined quality of completed innovations is lower. A 1 standard deviation increase in Time Burden decreases overall citations by 1.5%. In Column (2), I interact Time Burden with a Star Indicator, and find that Time Burden is negatively associated with both Stars' and Non-Stars' citations. A 1 standard deviation increase in Time Burden is associated with a 2.8% decrease in citations earned by Stars, and a statistically insignificant 1.1% decline in citations earned by Non-Stars. The difference between these coefficients is statistically significant (reported in the table's footer). This decline in citations is evidence that the overall quality produced by inventors, conditional on producing at least 1 patent, is lower. Further, because these are scaled citations, we can interpret this decline in quality as being relative to quite similar technologies.

In Columns (3) and (4), I use Citations per Patent as the dependent variable, as it captures the average impact of innovations completed. I find evidence that the average patent quality of a Star Inventor does not change, but that Non-Stars' average quality declines by 1%. Regulatory burden appears to drive Stars to focus on their "better" or higher quality projects, though they complete fewer. This means that Stars maintain the average quality of their inventors

in the face of rising regulatory burden. Non-Stars, however, appear to be producing similar patent volume, but of slightly lower average quality. Inference is similar when repeating the prior analyses using Unscaled Citations (Columns (5)-(8)), though statistical significance is greater and Non-Stars suffer more serious declines. Overall, regulatory burden lowers the observable quality (unscaled citations) of total and average innovation output, negatively affecting two readily available metrics inventors can use to distinguish themselves from others. Given that these metric are easily tracked and compared, similar to academic citations, inventors are largely worse off as regulatory burden rises.

In Table 4 Panel B, I examine how regulation may change the types of innovation inventors pursue (project selection) by examining citation-based measures of patent characterization. Generality uses patent citations to track the range of technology classes a patent influences, and Originality measures how wide a range of technology classes were incorporated into the patent itself (Trajtenburg et al. (1997)). I adjust both of these to account for biases created through citations, (Jaffe and Trajtenberg (2002), Hall (2005)). All columns use linear specifications. I find no evidence of decreased Generality, on average or within Star/Non-Star grouping. However, I find decreased Originality on average and within both groups; a 1 standard deviation increase in Time Burden decreases Originality by approximately 2%. There has been a persistent decline in the originality of innovations since about 2000 (Akcigit and Ates (2019)), and, according to my findings, increased regulatory burden may be one partial driver.

6.2.2 Text-based Measures

The citation results suggest an overall decline in patent quality generated by inventors and a narrowing of patent influence. Because citations are subject to certain distortion, like strategic citing (Lampe (2012)), patent examiner busyness and expertise (Righi and Simcoe (2019), Lei and Wright (2017)), and changing citation practices (Kuhn et al. (2020)), I examine text-based measures shown to be markers of novelty, impact, and scope, but unlikely to suffer the same distortions. These measures, aggregated from Arts et al. (2021), are the number of new terms introduced by an inventor's patents to the patent corpus, and how often subsequently filed patents reuse those terms.

In Table 5 Panel A, I regress the introduction of New n-grams (Scaled) on Time Burden, conditional on an inventor patenting in a given year. Panel A Column (1) shows a negative and weakly statistically significant relationship between New n-grams and Time Burden. In Panel A Column (2), I interact Time Burden with an indicator for whether the inventor is a Star. Consistent with the citations results, I find a highly statistically significant and negative coefficient on the interaction between Star and Time Burden. A 1 standard deviation increase in Time Burden decreases the number of New n-grams Introduced by Stars by about 3.1%. Adjusting for productivity (i.e., new n-grams per patent) produces statistically insignificant coefficients, but of the same sign as the citation results.

Because these measures are scaled by technology class and filing year, we can think of the patents produced by Stars as becoming less novel relative to patents in the same technology class. This finding is similar to the reduction in Originality in Table 4 Panel B, but is better thought of as an ex ante (i.e., known at time of publication) measure of impact. The projects of Stars become narrower as a result of regulatory burden.

In Table 5 Panel B, I examine how often subsequently filed patents reuse these New n-grams. Novelty should generally be important if it influences the language technological advancements use. If a patent introduces a new term, but other patents never use it, then that introduction has little scientific value. I again find that, on average, Time Burden has a weakly statistically significant, negative association, and that this average is driven by a decline in Stars. New terms introduced by Stars are reused less; a 1 standard deviation increase in Time Burden is associated with a 3.5% decrease in New n-grams Reused. The same increase in Time Burden is insignificantly associated with New n-gram Reuse for Non-Stars. A similar pattern, though statistically much stronger, appears in the Unscaled New n-gram Reuse measures. This indicates that, in addition to Star Inventors producing fewer patents, their general quality and novelty tend to decline as Time Burden increases.

Collectively, these results in citations and novel terms largely support the Strategic Innovation Hypothesis. On average, inventors' work narrows and becomes more incremental. Stars produce, in aggregate, lower innovation quality. Their projects on average, however, are no worse, suggesting they prioritize their best projects so as to minimize reputational de-

clines, which is slight evidence for the Risky Innovation Hypothesis. Non-Stars, on the other hand, complete narrower, less original projects. While there is little statistical significance in scaled citations, all Non-Star coefficients are negative, suggesting some deterioration of their output quality. Stars and Non-Stars' output alike receive fewer unscaled citations, and the declines in average, unscaled citations per patent are entirely concentrated in Non-Stars. Combined with the decline in new terms introduced to patent corpus, the results point to less breakthrough-oriented innovations and to more incremental discoveries.

6.3 Exploratory and Strategic Patenting

My citation and text-based impact results show an average decline in the quality and novelty of patents produced as regulatory burden declines. In this section, I examine whether this decline may be due to shifting focus from exploratory (or breakthrough) innovation towards more strategic and defensive innovations, in that employers direct their inventors to produce patents "protecting" their existing patent portfolios. A patent is essentially a government-granted legal monopoly over an invention, but the boundaries of this monopoly can be ill-defined until adjudicated by courts (Hall et al. (2015)).

In Table 6 Panel A, I focus on the exploratory innovation measures. In Column (1), Time Burden is negatively and statistically significantly related to the sum of RETech created. Column (2) shows that this is entirely concentrated in Star Inventor creations; a 1 standard deviation increase in Time Burden decreases RETech created by Stars by 6.2%. However, Star Inventors maintain the average RETech of their innovations, indicating similar "breakthrough" value per patent. In Columns (5)-(6), I find that Stars and Non-Stars are less likely to create Top Decile RETech patents as Time Burden increases, and that this effect is larger within Stars. A 1 standard deviation increase in Time Burden decreases the likelihood of a Star creating a top decile RETech patent by 0.6 percentage point (2.8%). I examine Breadth in Columns (7)-(8). Constant across Stars and Non-Stars alike, Time Burden exhibits a negative and statistically significant relationship with Breadth. A 1 standard deviation increase in Time Burden is associated with a 2.6% (1 pp) decline in Breadth, which matches the results on citation-based Originality. Holistically, Time Burden is negatively associated with breakthroughs, and

narrows the innovative focus of inventors.

In Table 6 Panel B, I study measures of strategic patenting. In Column (1), I find a positive but statistically insignificant relationship between Time Burden and average self-cite ratio. This is also the case when separating Stars from Non-Stars in Column (2). In Columns (3)-(4), I examine the likelihood of filing for a 'defensive' patent (above average self-cite ratio). There is a statistically significant negative association in Star patenting; a 1 standard deviation increase in Time Burden results in a 1.5% (1.0 pp) decrease in likelihood of creating at least 1 defensive patent (conditional on patenting at all). I find similar evidence of slight declines in process patenting in Columns (5)-(8). A Star is ≈1.3% (0.8 pp) less likely to produce a process patent.

Collectively, the results in Table 3 and Table 4 show that regulatory burden decreases the quantity and quality of innovations produced by inventors. However, in Table 6 Panels A and B, I find little compelling evidence that this decline is driven by strategic patenting. Instead, it seems that the focus of individual inventors does not change, but the quantity and likelihood of technological breakthroughs declines as regulatory burden increases.

6.4 Inventor Mobility And Teams

6.4.1 Individual Turnover

In this section, I evaluate the Disutility and Human Capital Hypotheses. If regulatory burden is disruptive and takes time away from innovation activities, inventors should change jobs to avoid this situation, leveraging their market power to find more desirable positions. However, if inventors develop regulation-specific human capital through their government engagements, their skills may make them more valuable to their teams (and the firm), decreasing their propensity to leave their employer.

In Table 7 Panel A, I regress an indicator for whether the inventor moves from one assignee to another. I find that a 1 standard deviation increase in Time Burden is associated with a 2% increase in the likelihood of a job change, across a wide range of specifications. This evidence supports the Disutility Hypothesis, suggesting inventors change jobs to escape high levels of compliance paperwork. In Panel A Column (6), I find evidence that Stars are similarly more

likely to change jobs in response to increases in regulatory burden. A 1 standard deviation increase in Time Burden is associated with a 0.2 percentage point (1.2%) increase in likelihood of a Star changing jobs, roughly 30% of the economic magnitude of an equivalent decline in prior productivity. The economic magnitude is, however, significantly smaller than an equivalent change in experience (≈7% of the magnitude). For additional context, Baghai et al. (2021) find a 52% (6.7pp) increase in the likelihood of skilled workers to leave a firm as it approaches bankruptcy. Hombert and Matray (2017) find a 30% (3.9pp) increase in the likelihood of an inventor moving from a small firm to a large firm, following a negative shock to the small firm's lending relationships. It is reasonable to expect compliance burden to have smaller effect sizes than one's employer sliding into bankruptcy.

I find similar evidence that Non-Stars' propensity to change jobs increases as Time Burden increases. The Non-Star coefficient is not significantly different from that of Stars (p-value reported in the table's footer). Collectively, these results provides additional evidence of regulatory burden affecting the labor component of innovation, in that firms are less able to retain their most productive (and important) inventors as regulatory burden increases.

In Table 7 Panel B, I examine whether inventors are more likely to move to larger employers, and their likelihood of moving internally. I first regress an indicator for an inventor moving to an employer with more inventors than their previous employer on regulatory burden. I find on average, a positive and statistically significant relationship; a 1 standard deviation increase in Time Burden is associated with a 0.2pp (4.4%) increase in the likelihood of moving to a larger firm. In Column (2), I show this is concentrated entirely in Non-Star Inventors. In Column (3), I repeat the analysis in Column (2), but condition the sample on changing jobs, and find that both Stars and Non-Stars are more likely to move to larger firms as burden increases. In Columns (4)-(6), I examine whether burden increases within-employer transitions, i.e. an inventor remaining with the same employer but moving to a different city. I find some evidence that this is the case for Non-Stars (0.1pp, compared to 5.3pp unconditional), but the association is negative in Stars (-0.2pp, compared to 10.3pp unconditional).

Collectively, these mobility results support the Disutility Hypothesis, and suggest that inventors change jobs to lessen their burden. Inventors appear to have some preference for

larger employers, as size may partially mitigate the disutility of regulatory burden.

6.4.2 Team Stability

Next, I examine how an inventor's team changes as compliance burden increases. As inventor mobility increases, we can expect the formation and dissolution of teams to increase. This could be disruptive, as team stability is known to be beneficial (Jaravel et al. (2018), Chen (2021)). Increased mobility also suggests the aggregate size of inventor teams could fluctuate. Increased Team Size could speak to the additional burden of innovation, and suggest firms respond to burden by hiring additional inventors. Decreased Team Size may suggest that inventors leave more quickly than firms can hire new ones.

I construct several measures of an inventor's team size. First, I count the number of distinct inventors she works with when she is productive (i.e., produces a patent). 'Coauthors' is thus the sum of unique coauthors an inventor files patents in a year. I also count the number of new coauthors each year, and calculate the fraction of an inventor's team which is "new" to her. The first measure captures the breadth of an inventor's 'team' in aggregate; they must coordinate with all of these people in order to generate innovation. The second captures within-team(s) turnover, and measures stability (or lack thereof).

I report results of Poisson regressions in Table 8 Panel A, where the dependent variable is the sum of coauthors worked with, conditional on patenting. Column (1) shows a negative and statistically significant coefficient; the economic magnitude, however, is small. A 1 standard deviation increase in Time Burden decreases Team Size by 1%, and the average team size is 4.4 inventors. I then interact Time Burden with Star Status, and find the effect is stronger in Stars. A Star works with about 9 other coauthors, conditional on patenting, and a 1 standard deviation increase in Time Burden decreases this by ≈ 0.25 inventors. Columns (3)-(6) consider whether this is driven by differences between domestic and foreign employers, and find slightly larger magnitudes in Foreign Employers. In practice, inventors work with marginally smaller teams as a result of increases in compliance burden.

In Table 8 Panel B, I examine within-team turnover by regressing the fraction (count) of new coauthors on Time Burden. All columns report coefficients from OLS specifications.

Column (1) shows that the average effect is negative, small, and statistically insignificant. However, separating Stars from Non-Stars reveals statistically significant heterogeneity. A 1 standard deviation increase in Time Burden increases a Star's fraction of new coauthors by 0.4 percentage points (1.1%). In Columns (3)-(4), I show that this is concentrated in Domestic Employers, though overall, the economic magnitudes are somewhat small.

Taken together with Panel A, these results suggest that Star Inventors' within-team turnover increases; the total number of coauthors declines, and the fraction of new members increases. Integrating new coauthors into workflows and projects is costly, and this could be a contributing factor to the overall fall in Star productivity.

7 Robustness

7.1 Technological Differences

7.1.1 Technology Class-by-Year FE

In Table 9 Panel A, I add technology class-by-year fixed effects to my most stringent specifications.[17] In Columns (1)-(6), I include CPC Section-by-Year fixed effects (e.g. CPC Section C). This is a less granular technology classification than my measure is constructed from, and compares inventors working on broadly similar technologies. In Column (7)-(12), I include CPC Class-by-Year fixed effects (e.g. CPC Class C07). These fixed effects remove trends of an inventor's primary technology class, exploiting variation related to her secondary technology classes. I define an inventor's primary CPC Class as the Class she patents in (historically) most often. While inventor fixed effects absorb the average maturity of a technology class during that inventor's tenure, and firm-by-year fixed effects absorb how a firm's industry matures, these technology class-by-year fixed effects absorb directly the changes in technology class maturity.

I find results economically and statistically similar to my main analyses. A 1 standard deviation increase in Time Burden is associated with a 2.1-3.6% decline in productivity, a 1.5-

17. I also report additional technology class-by-year fixed effect specifications in Table A7, namely using Employer-by-Year-by-Tech Class fixed effects.

1.7% decline in scaled citations, and a 2% increase in inventor mobility. Star Inventors drive productivity losses (14.0-14.6% decline) and the overall decline in scaled citations. Non-Stars drive the increased likelihood of changing jobs, though the coefficient is no different from that of Stars.

7.1.2 Rapidly Evolving Technology Fields

To examine this maturity hypothesis in a different manner, I use the rapidly evolving technology (RETech) measure developed by Bowen et al. (2022), and create a stock of RETech for each CPC Class over time:

$$\text{RETech}_{(c,t)} = \frac{1}{\text{P}_{(c,t)}} \sum_{p \in \text{P}_{(c,t)}} (1-d)^{k(p)} \text{RETech}(p)$$

where $\text{P}_{(c,t)}$ represents the patents filed in a CPC class over the preceding 5 years, $k(p)$ is the number of years since patent p was filed, and $\text{RETech}(p)$ is the RETech of patent p. I use an annual depreciation rate of 20%, as this is commonly used for R&D expense and innovation settings (Bowen et al. (2022), Fresard et al. (2019), Peters and Taylor (2017)). All RETech values at the patent-level are winsorized at the 1st and 99th percentiles (by year) before aggregation (recommended by Bowen et al. (2022)). The intuition is that high RETech patents displace current technology, and so a high 'stock' of RETech at the CPC Class-level indicates a field is rapidly changing. Low values indicate a more mature or stable technology class. I define "Rapidly Evolving Technology Class" as a CPC Class in the top decile of RETech Stock per year. I define an inventor's primary CPC Class as the Class she patents in (historically) most often.

In Table 9 Panel B, I examine my primary results (productivity, citations, and mobility) separately for inventors working in rapidly evolving technology classes (Columns (1)-(6)) and those in mature technology classes (Columns (7)-(12)). I only report results net of time-invariant inventor characteristics and employee-by-location trends (my most stringent specification), and I find similar results for both groups of inventors to my primary results. Specifically, in Column (1), a 1 standard deviation increase in Time Burden is associated with a 2.3%

decrease in productivity for inventors in high RETech classes. As in my baseline tests, this decline is concentrated in Star Inventors, who experience a 12.5% decline (Column (2)). In Column (7), a 1 standard deviation increase in Time Burden is associated with a 2.1% decline in productivity for inventors in mature technology classes. Stars experience a 14% decline in productivity for the same increase. Note that the annual productivity (listed in the table's footer) of Stars and Non-Stars between each technology class grouping is similar.

An inventor's accrued citations differ based on whether she is working in a high RETech or mature technology class. On average, there is a negative association between Time Burden and citations, though it is only statistically significant in high RETech classes. Both Stars and Non-Stars are similarly negatively affected. The findings are consistent with Table 4 Panel A, and are in opposition to the regulatory regime maturity argument, i.e., that declines in citations would be concentrated in mature technology classes.

The mobility results also differ depending on whether an inventor is working in a rapidly evolving or mature technology class. Time Burden is positively associated with a 2% increase in mobility in rapidly evolving technology classes, but the coefficients are only approaching conventional levels of statistical significance. Time Burden is positively and statistically significantly related to mobility in mature technology classes, and affects Stars and Non-Stars similarly (a 1.7% and 1.1% increase, respectively). This is weak evidence in support of the regulatory regime hypothesis.

In sum, I find little evidence that my primary results are driven by the maturity of regulatory regime in a technology class. Time Burden is negatively associated with productivity in all technology classes. The citation and mobility results, while different from each other, are consistent with my primary results, and taken together, do not substantively support the regulatory regime maturity hypothesis.

7.1.3 Changing Patenting Practices

Patenting practices also differ across technology fields; Lerner and Seru (2021) document a surge in granted patents related to Chemical and Software patents beginning in the 1990s. This raises two concerns. First, sharp increases in these types of patents may precede increases

in regulation in these technology fields, and, given an uncertain lag structure, could explain a negative association between Time Burden and productivity. Second, Star Inventors may be concentrated in these technology fields, and so the differential impact on Stars vs Non-Stars may be driven by regulatory burden primarily affecting "Chemistry" and/or "Software" inventors.

I define "Chemistry" inventors as those who patent in CPC Section "Chemistry / Metallurgy" and "Software" inventors as those who patent in CPC Class "Computing; Calculating or Counting" and "Information and Communication Technology." I define an inventor's primary CPC Section (Class) as the Section (Class) she patents in (historically) most often. These inventors comprise approximately 25% of the sample.

In Table 9 Panel C, I omit these inventors from the sample, as recommended by Lerner and Seru (2021). I find comparable results to my main analyses, in both economic magnitude and differential impact. A 1 standard deviation increase in Time Burden is associated with a 2.4% decline in productivity, a (statistically insignificant) 1.2% decline in scaled citations, and a 1% increase in inventor mobility. Star Inventors drive productivity losses (14% decline) and suffer a statistically significant decline in citations. All inventors are more likely to move jobs in response to increases in burden, but the size of the response is no different between Stars and Non-Stars.

7.2 Alternative Star Definitions

I also report results using different measures of "Star Inventors." In my main specifications, I use the 95^{th} percentile of patent production over the preceding decade. In these analyses, I redefine "Star" using the 90^{th} and 99^{th} percentiles of patent production over the preceding decade, as well as the 90^{th}, 95^{th}, and 99^{th} percentiles of accumulated scaled citations over the previous decade, to show similarity of coefficient across definitions (Moretti and Wilson (2017), Akcigit et al. (2016)). My baseline results are robust to these alternative definitions.

In Table 10 Panel A, I regress inventor-level patent count on Time Burden interacted with each Star definition. The column's header reports how "Star" is defined. In all columns, the coefficient on Time Burden $\times$ Star is negative and statistically significant, indicating a

12.3%-13.9% decline in productivity. Non-Stars exhibit a positive and statistically significant response in 3 of 6 specifications, a negative and statistically significant response in 2 specifications, and a statistically insignificant response in the remaining. The coefficients range between a 1.3% decline to 2.8% increase in productivity, or approximately 0.01 fewer patents per year to 0.015 more patents per year. The difference between Star and Non-Star coefficients is always highly statistically significant.

In Table 10 Panel B, I examine (scaled) citations, conditional on patenting, as a proxy for innovation quality. As Time Burden increases, Stars' inventions receive fewer citations; the coefficients are negative in all 6 specifications and statistically significant in 5 specifications. The size of the decline ranges between 2.8% and 8%. Non-Stars, on the other hand, exhibit statistically insignificant effects in 4 of 6 specifications. The remaining two are a 1.4% decline in quality and a 2.8% increase. The difference between Stars and Non-Stars is different in 5 of 6 specifications. I consistently find evidence that, conditional on patenting, Star patents are of lower quality as burden increases, driving declines in overall patent quality declines.

In Table 10 Panel C, I examine inventor mobility. Stars are more likely to change jobs in response to increases in Time Burden in 5 of 6 specifications. The coefficients represent 0.2pp to 0.5pp increase in likelihood, or about 1.2% to 2% increase relative to the likelihood of changing jobs conditional on being a Star. Non-Stars always exhibit a positive and statistically significant response, and the magnitude is quite stable at 0.2pp (2.2%). The Star and Non-Star coefficients are statistically no different from each other in all specifications.

Taken together, I find a differential impact of Time Burden between Star and Non-Stars across varying definitions of "Star"-dom, whether by patent output or citation accumulation, consistent with my primary analyses.

7.3 Compliance Support

A key assumption underpinning my results is that it is difficult for inventors to outsource the paperwork burden associated with their work to other parties within the firm, e.g., regulatory compliance specialists and other administrative staff. Stated differently, even with substantial support staff, compliance work detracts from the time an inventor spends innovating,

whether inventors personally respond to federal agencies or relay information about innovative projects to compliance staff. To assess this more formally, I analyze a group of inventors expected to have greater compliance support: those working for U.S. Publicly Traded Firms.

To identify public firms, I use the A. Arora et al. (2021) and Ewens and Marx (2023) link-tables. I then examine just these public firm inventors in Table 11, reporting analyses for inventor productivity, scaled citations, and mobility. I find results consistent with my baseline tests, though the magnitudes are dampened as one might expect. Public Firm Inventors exhibit lower productivity, on average, in response to increases in Time Burden, and this decline is driven by Stars. The Star magnitude is slightly smaller than the overall sample magnitude (-11.7% in public firms vs -13.9% overall). Similarly, inventors are more likely to change jobs as Time Burden increases, and this is present in both Stars and Non-Stars. For citations, the overall average and the effect of Time Burden within Stars is negative and of similar magnitude to Table 4 Panel A, however neither is statistically significant at conventional levels.

7.4 Known Issues in Patent Data

7.4.1 Truncation

Patent data naturally suffers truncation bias. As of May 2024, the USPTO reports an average 'First Office Action Pendency' of 20 months, meaning the time between patent filing and the USPTO first considering the application. The USPTO 'disposes' of applications (renders decisions) on average within 26 months, but the process can take significantly longer depending on the technology center or whether the applicant files Requests for Continued Examination.[18] This delay between filing and granting leads to 'truncation bias' in both patent counts and forward citations; this bias is most severe in the most recent years of any panel. Lerner and Seru (2021) recommend trimming the most recent years of the sample, motivating why my primary results end in 2020. However, they recommend for robustness to use significantly less data, so I rerun my patent and citation analyses on a sample comprised of 1993 to 2014 (an even two decades of data, when using control variables lagged by 1 year).

18. Current pendency data available at the USPTO website

In Table 12 Panel A, I report results using my most stringent specification and the reduced sample. The patent count panel is approximately one-sixth smaller, and the citation sample is approximately 30% smaller. The results are quite similar to my baseline specifications. A 1 standard deviation increase in burden is associated with a 2% decline in patent counts and a 1.7% decline in scaled citations (conditional on patenting). These declines are both concentrated in Star Inventors, who are 13.8% less productive and accrue 3.5% fewer scaled citations.

7.4.2 High Tech Clusters

Certain regions are known for their outsized influence on both U.S. and worldwide innovation output and impact (Moretti (2021)), and this effect can lead to bias in empirical research in panel settings (Lerner and Seru (2021)). For example, California and Massachusetts are innovation hubs, and their inventors comprise about 14% of the total sample and 28% of the US-based sample. In Table 12 Panel B, I examine whether observations in these states drive my productivity and citation results by excluding them from the analyses. I first examine the association between Time Burden and productivity. In Column (1), a 1 standard deviation increase in Time Burden is associated with a 1.9% reduction in productivity, for all the inventors not living in California or Massachusetts. In Column (2), I split the sample into Stars and Non-Stars, and find the reduction is concentrated in Stars (a 14.0% decline). Overall, all coefficients are very similar to those in Table 3. Likewise, the scaled citations results in Columns (3)-(4), in terms of statistical and economic magnitude, are similar to those in Table 4.

7.5 Alternative Clustering of Standard Errors

I cluster standard errors by inventor and assignee in my primary specifications because the treatment variation central to my hypotheses varies within inventor over time, and there may be correlations between inventor clusters within assignee (Petersen (2008)). However, there are other motivations for determining the level(s) of clustering (e.g., common shocks within a year (cross-sectional dependence) (Cameron et al. (2011),Petersen (2008), Thompson (2011))) with the general concern being that fixed effects do not absorb all within and between correlation of residuals. To address this concern empirically, I repeat my primary analyses in

Table 13, and report standard errors adjusted for multi-way clustering at the inventor and assignee-year level, as well as single clustering at the inventor-level (Abadie et al. (2022)). Columns (1)-(3) report productivity analyses, Columns (4)-(6) report citation analyses, and Columns (7)-(9) report mobility analyses. Each column heading reports the level of clustering. Columns (1), (4), and (7) report t-statistics for standard errors clustered at the inventor-level, addressing autocorrelation within individual inventors. Columns (2), (5), and (8) report t-statistics for standard errors clustered at the inventor and assignee-year level, to account for common shocks within an assignee-year. Finally, Columns (3), (6), and (9) (my primary specifications from Table 3, Table 4, and Table 7) adjust standard errors to account for time-series dependence of inventor clusters within firm. All specifications report similarly high levels of statistical significance, as well as similar differences (reported in the table's footer) between Star and Non-Star coefficients.

8 Conclusion

This paper uses a subset of regulatory burden estimates, namely the federal government's administrative agency burden (not state or municipality), and asks how this burden impacts patent-producing inventors. I find that regulatory burden decreases the quantity of innovation produced. This evidence informs how regulators should not only consider the burden of an individual rule, but the aggregate burden imposed by all regulations. Viewed in isolation, an agency may approve of a new rule on the grounds that it requires "only" 1-2 hours per engagement with each respondent. However, this marginal increase has consequences, as inventors burdened by regulations are willing to leave employers to avoid the disutility of this compliance burden. This evidence suggests that the aggregate burden of regulation affects the wedge between inventors and employers, increasing turnover to the detriment of innovation. Collectively, these findings show how the administrative state imposes costs on innovative activities, and how compliance burden changes the type and quality of patents ultimately granted.

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Figure 1: **Selecting k Topics for STM**

Structural topic models of varying k are trained on the text of paperwork regulations, and the model is chosen using visual inspection of common performance metrics. Exclusivity (mean of all topics per model) measures whether common words within a topic are common across all topics (Bischof and Airoldi (2012)). Perplexity (i.e., held-out likelihood Roberts et al. (2019)) scores how well the model predicts words removed from a random sample of regulations. Residual Dispersion (Taddy (2012)) evaluates the degree of overdispersion of the STM residuals. Semantic Coherence (mean of all topics per model, Mimno et al. (2011)) scores how understandable the theme of a topic is to human readers. The selected model ($k = 150$) minimizes residual dispersion (Silge (2018)) and has similar perplexity to other models of similar residual dispersion. Exclusivity naturally tends to increase as additional topics are created, and Semantic Coherence tends to decline.

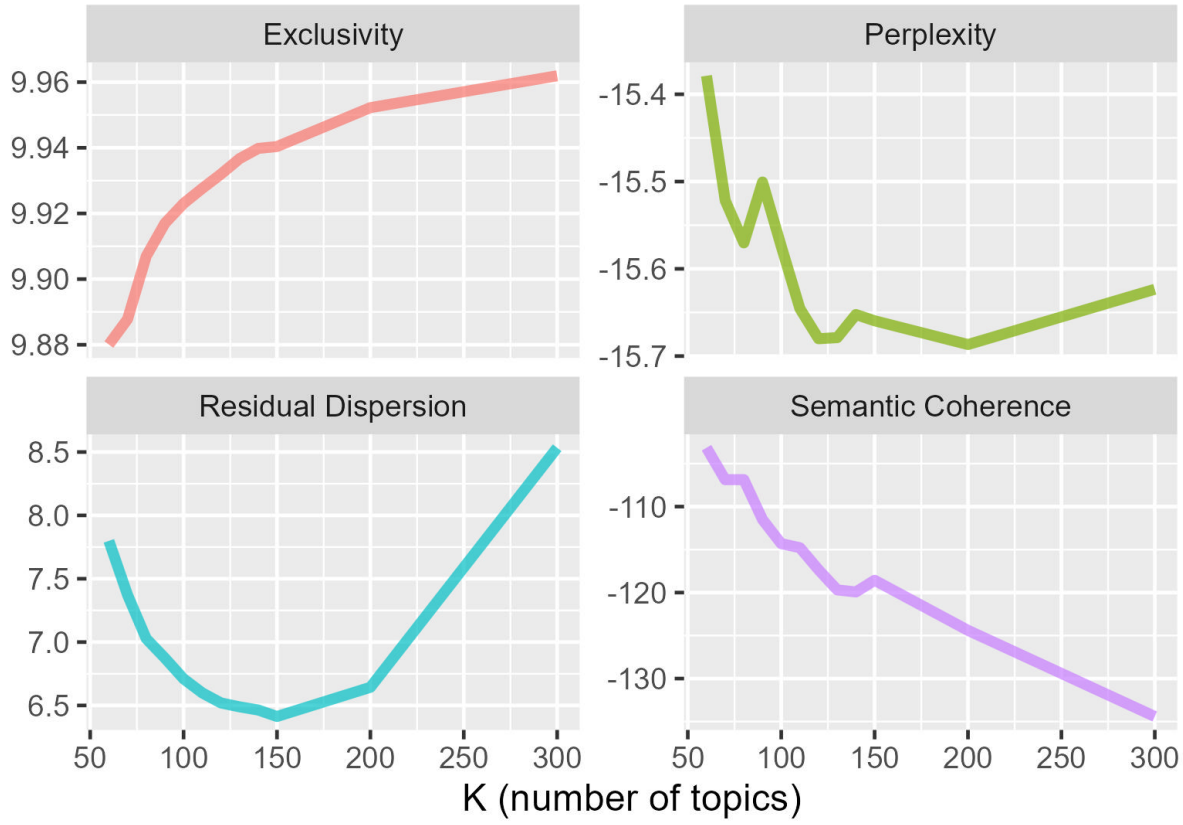
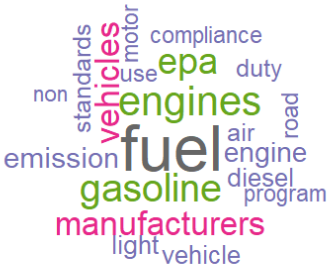


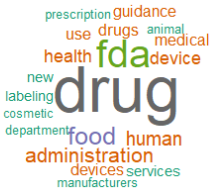
Figure 2: **Topic Clouds**

The text of paperwork regulations is categorized into 150 topics using structural topic modeling. Word clouds of the most frequently appearing words in selected topics are reported below.

(a) Topic 63



(b) Topic 98



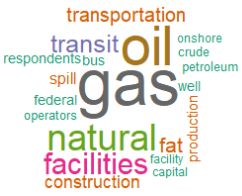
(c) Topic 104



(d) Topic 119



(e) Topic 135



(f) Topic 136



Figure 3: **CPC Section Burden Over Time**

This figure reports the average Time Burden for each Cooperative Patent Classification Section (i.e., the broadest level of patent technology class) over time. Time Burden is winsorized at the 1st and 99th percentiles, standardized, and finally normalized to a mean of 100.

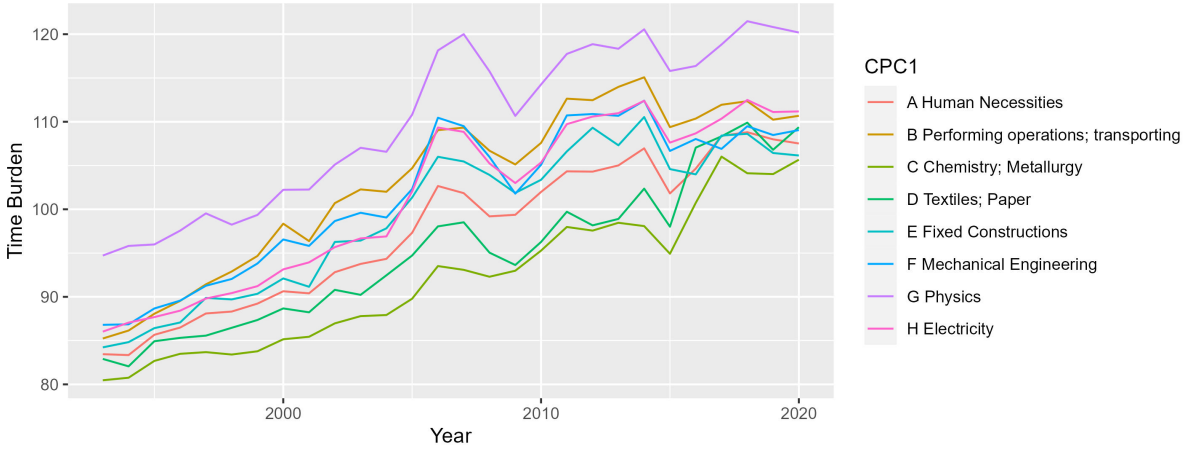


Table 1: **Correlations Between Text-based Regulatory Measures**

This table reports pairwise correlations between various measures of regulatory burden and regulatory restrictiveness. "Time Burden" and "Paperwork Burden" are the inventor-specific measures created in this paper. "RegIn_Regulations", "RegIn_Responses", and "RegIn_Time" are public firm-specific measures of regulatory intensity created by Kalmenovitz (2023). "Restrictions$_{CFR}$" and "Conditionals$_{CFR}$" are, respectively, the annual sum of "Restrictive" words and annual sum of "Conditional" words per 100 sentences in the Code of Federal Regulations (CFR), created by Al-Ubaydli and McLaughlin (2017) and housed by the George Mason University Mercatus Center. Restrictive words are "shall," "must," "may not," "prohibited," and "required." Conditionals are "if," "but," "except," "provided that," "when," "where," "whenever," "unless," "notwithstanding," "in the event," "in no event," and "to the extent that." All correlations are highly statistically significant.

Correlation Table

	Time Burden	Paperwork Burden	RegIn_Regulation	RegIn_Responses	RegIn_Time	Restrictions$_{CFR}$	Conditionals$_{CFR}$
Time Burden	1						
Paperwork Burden	0.280***	1					
RegIn_Regulation	0.630***	0.294***	1				
RegIn_Responses	0.561***	0.266***	0.844***	1			
RegIn_Time	0.554***	0.287***	0.841***	0.929***	1		
Restrictions$_{CFR}$	0.650***	0.280***	0.783***	0.824***	0.776***	1	
Conditionals$_{CFR}$	0.476***	0.448***	0.554***	0.474***	0.486***	0.524***	1

Table 2: **Summary Statistics**

This table reports summary statistics for key variables used in the inventor-level analyses. All continuous variables are winsorized at the 1st and 99th percentiles within Star grouping.

Summary Statistics

	Mean	St. Dev.	P5	P10	P25	Median	P75	P90	P95
Patent Count	0.815	2.075	0.000	0.000	0.000	0.000	1.000	2.000	3.000
Cites (Scaled)	1.333	6.177	0.000	0.000	0.000	0.294	1.071	2.962	5.336
Cites (Scaled) / Patent	0.607	1.622	0.000	0.000	0.000	0.197	0.624	1.471	2.417
Cites (Unscaled)	19.022	131.227	0.000	0.000	0.000	2.000	11.000	37.000	74.000
Cites (Unscaled) / Patent	8.901	34.938	0.000	0.000	0.000	1.250	6.000	19.160	36.500
Generality	0.360	0.340	0.000	0.000	0.000	0.333	0.667	0.833	1.000
Originality	0.536	0.334	0.000	0.000	0.281	0.600	0.810	0.946	1.000
New n-grams (Scaled)	4.797	19.904	0.000	0.000	0.000	0.422	3.279	11.217	21.727
New n-grams (Scaled) / Patent	2.194	8.076	0.000	0.000	0.000	0.281	1.913	5.188	9.332
New n-grams Reuse (Scaled)	4.827	24.386	0.000	0.000	0.000	0.279	2.912	10.304	20.712
New n-grams Reuse (Scaled) / Patent	2.132	9.183	0.000	0.000	0.000	0.195	1.688	4.836	8.862
New n-grams (Unscaled)	4.879	24.715	0.000	0.000	0.000	1.000	4.000	11.000	20.000
New n-grams (Unscaled) / Patent	2.373	11.826	0.000	0.000	0.000	0.333	2.000	5.250	9.000
New n-grams Reuse (Unscaled)	18.731	219.087	0.000	0.000	0.000	2.000	10.000	36.000	70.000
New n-grams Reuse (Unscaled) / Patent	8.909	99.226	0.000	0.000	0.000	1.000	6.000	18.000	34.000
Sum(RETech)	2.217	4.115	-0.801	-0.279	0.378	1.148	2.607	5.435	8.748
RETEch per Patent	1.096	1.434	-0.605	-0.219	0.300	0.829	1.545	2.688	3.676
1(Top RETech Decile Patent)	0.137	0.344	0.000	0.000	0.000	0.000	0.000	1.000	1.000
Technological Breadth	0.384	0.230	0.017	0.031	0.168	0.438	0.577	0.661	0.695
Self-Cite Ratio	0.119	0.205	0.000	0.000	0.000	0.000	0.167	0.389	0.547
1(Defensive Patent)	0.377	0.485	0.000	0.000	0.000	0.000	1.000	1.000	1.000
Scaled Process Claims per Patent	1.028	1.576	0.000	0.000	0.000	0.609	1.435	2.531	3.531
1(Process Patent)	0.438	0.496	0.000	0.000	0.000	0.000	1.000	1.000	1.000
1(Change Job)	0.100	0.300	0.000	0.000	0.000	0.000	0.000	1.000	1.000
1(Move Employer Larger)	0.045	0.207	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1(Move Internal)	0.055	0.228	0.000	0.000	0.000	0.000	0.000	0.000	1.000
1(US-based Inventor)	0.510	0.500	0.000	0.000	0.000	1.000	1.000	1.000	1.000
1(U.S. Firm)	0.476	0.499	0.000	0.000	0.000	0.000	1.000	1.000	1.000
1(Foreign Firm)	0.447	0.497	0.000	0.000	0.000	0.000	1.000	1.000	1.000
1(Self-employed)	0.042	0.201	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1(University)	0.025	0.155	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1(Government)	0.011	0.103	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Time Burden	100.303	9.362	85.354	87.649	93.063	100.712	106.845	111.880	114.160
Paperwork Burden	99.975	8.392	86.923	91.574	96.052	98.126	101.340	113.590	118.541
Ln(Experience)	2.111	0.802	0.693	1.099	1.386	2.197	2.773	3.178	3.332
Ln(Prior Prod.)	1.115	0.808	0.000	0.000	0.693	1.099	1.609	2.197	2.565
Ln(Years Since Prev. Patent)	0.833	0.856	0.000	0.000	0.000	0.693	1.386	2.079	2.485
1(Indiv. Assignee)	0.002	0.048	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	12,564,053								

Table 3: **Inventor Productivity**

The dependent variable is the inventor-level count of patents produced. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns report Poisson Pseudo Maximum Likelihood estimations.

Panel A: Full Sample

	Patent Count					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.017***	-0.022***	-0.021***	-0.024***	-0.020***	
	(-4.56)	(-4.60)	(-5.30)	(-6.52)	(-5.40)	
T.Burden x Star						-0.150***
						(-19.80)
T.Burden x Non-Star						0.011***
						(2.87)
1(Star)						0.542***
						(21.26)
Ln(Experience)					0.184***	0.168***
					(24.95)	(24.82)
Ln(Yr. Since Prev. Pat.)					-0.038***	-0.035**
					(-2.60)	(-2.48)
1(Indiv. Assignee)					0.004	-0.003
					(0.09)	(-0.05)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	No	No	No	No	No
Year FE	Yes	No	No	No	No	No
Employer-by-Year FE	No	Yes	Yes	No	No	No
City FE	No	No	Yes	No	No	No
Employer-by-City-by-Year FE	No	No	No	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Star=Non-Star (p-value)						0.000
$\bar{y}$	0.815	0.815	0.815	0.815	0.815	
Star $\bar{y}$						4.376
Non-Star $\bar{y}$						0.619

Panel B: Sub-sample Heterogeneity

	US-based		Foreign-based		Domestic Assignee		Foreign Assignee	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Burden	-0.017**		-0.020***		-0.019**		-0.021***	
	(-2.43)		(-4.55)		(-2.47)		(-4.58)	
T.Burden x Star		-0.128***		-0.164***		-0.124***		-0.166***
		(-10.71)		(-18.26)		(-10.12)		(-18.28)
T.Burden x Non-Star		0.012*		0.011**		0.011		0.012***
		(1.82)		(2.42)		(1.46)		(2.70)
1(Star)		0.456***		0.591***		0.429***		0.605***
		(10.98)		(19.52)		(9.44)		(20.61)
Ln(Experience)	0.158***	0.150***	0.191***	0.171***	0.144***	0.136***	0.190***	0.169***
	(18.95)	(18.30)	(16.92)	(16.96)	(16.11)	(17.13)	(15.98)	(16.12)
Ln(Yr. Since Prev. Pat.)	0.029	0.030	-0.077***	-0.073***	0.017	0.017	-0.084***	-0.080***
	(1.18)	(1.23)	(-5.47)	(-5.25)	(0.76)	(0.80)	(-5.98)	(-5.75)
1(Indiv. Assignee)	-0.159*	-0.158*	0.053*	0.044	-0.051	-0.051	0.065**	0.055*
	(-1.67)	(-1.66)	(1.65)	(1.35)	(-1.47)	(-1.48)	(2.10)	(1.78)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6,403,890	6,403,890	6,160,163	6,160,163	5,980,942	5,980,942	5,598,886	5,598,886
Star=Non-Star (p-value)		0.000		0.000		0.000		0.000
$\bar{y}$	0.808		0.822		0.857		0.840	
Star $\bar{y}$		4.464		4.287		4.505		4.282
Non-Star $\bar{y}$		0.609		0.629		0.644		0.636

Table 4: **Patent Citation Measures**

The dependent variables are citation-based measures of patent impact (citations and citations per patent) and characterization (generality and originality), at the inventor-year level. The variables of interest are Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. Columns (1)-(4) use citations scaled by the average number of citations received by patents in that technology class and filing year. All columns in Panel A report Poisson Pseudo Maximum Likelihood estimations. Panel B reports OLS specifications.

Panel A: Citation-based Impact (Poisson)

	Scaled Citations				Unscaled Citations			
	(1) Cites	(2) Cites	(3) Cites/Patent	(4) Cites/Patent	(5) Cites	(6) Cites	(7) Cites/Patent	(8) Cites/Patent
Time Burden	-0.015*		-0.007		-0.030***		-0.023***	
	(-1.84)		(-1.36)		(-3.20)		(-3.33)	
T.Burden x Star		-0.028**		0.010		-0.027**		0.002
		(-2.38)		(1.29)		(-2.08)		(0.17)
T.Burden x Non-Star		-0.011		-0.010*		-0.032***		-0.027***
		(-1.32)		(-1.91)		(-3.40)		(-3.92)
1(Star)		-0.005		-0.085***		-0.076**		-0.099***
		(-0.16)		(-4.29)		(-2.26)		(-4.38)
Ln(Experience)	-0.023**	-0.027**	-0.044***	-0.042***	-0.015	-0.016	-0.042***	-0.039***
	(-2.09)	(-2.50)	(-7.74)	(-7.57)	(-1.27)	(-1.38)	(-6.75)	(-6.10)
Ln(Prior Prod.)	0.017	0.031***	-0.030***	-0.027***	-0.005	0.008	-0.036***	-0.034***
	(1.60)	(2.96)	(-8.47)	(-7.50)	(-0.46)	(0.78)	(-7.53)	(-6.82)
Ln(Yr. Since Prev. Pat.)	-0.082***	-0.076***	-0.001	-0.000	-0.084***	-0.078***	-0.004	-0.004
	(-13.48)	(-12.17)	(-0.42)	(-0.13)	(-10.28)	(-8.78)	(-1.02)	(-0.96)
1(Indiv. Assignee)	-0.010	-0.010	-0.017	-0.015	-0.045	-0.043	-0.066	-0.065
	(-0.30)	(-0.30)	(-0.57)	(-0.52)	(-1.05)	(-1.02)	(-1.54)	(-1.50)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496
Star=Non-Star (p-value)		0.079		0.002		0.662		0.000
$\bar{y}$	1.333		0.607		19.022		8.901	
Star $\bar{y}$		4.103		0.746		59.767		11.658
Non-Star $\bar{y}$		1.001		0.590		14.133		8.570

Panel B: Citation-based Characterization (OLS)

	Generality		Originality	
	(1)	(2)	(3)	(4)
Time Burden	-0.002		-0.010***	
	(-1.23)		(-8.51)	
T.Burden x Star		0.000		-0.008***
		(0.15)		(-5.43)
T.Burden x Non-Star		-0.002		-0.010***
		(-1.43)		(-8.72)
1(Star)		-0.007*		-0.007**
		(-1.70)		(-2.14)
Ln(Experience)	-0.006***	-0.006***	0.003***	0.003***
	(-6.47)	(-5.85)	(3.60)	(3.84)
Ln(Prior Prod.)	-0.003***	-0.003***	-0.002***	-0.002***
	(-4.51)	(-5.26)	(-5.94)	(-5.55)
Ln(Yr. Since Prev. Pat.)	0.000	0.000	-0.000	-0.000
	(0.64)	(0.24)	(-0.85)	(-0.84)
1(Indiv. Assignee)	0.005	0.005	0.000	0.000
	(0.68)	(0.69)	(0.04)	(0.06)
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	3,388,458	3,388,458	4,810,163	4,810,163
Star=Non-Star (p-value)		0.019		0.047
$\bar{y}$	0.361		0.536	
Star $\bar{y}$		0.333		0.488
Non-Star $\bar{y}$		0.365		0.542

Table 5: **Patent Text Measures**

The dependent variables are text-based measures of patent characterization (new n-grams and new n-grams per patent) and impact (new n-gram reuse and new n-gram reuse per patent), at the inventor-year level through 2017. The variables of interest are Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in the prior year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized.

Panel A: Text-based Characterization (Poisson)

	New n-grams (Scaled)				New n-grams (Unscaled)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nn	Nn	Nn/Patent	Nn/Patent	Nn	Nn	Nn/Patent	Nn/Patent
Time Burden	-0.013*		-0.003		-0.030***		-0.017***	
	(-1.83)		(-0.42)		(-5.16)		(-3.45)	
T.Burden x Star		-0.031***		0.014		-0.027***		0.010
		(-3.05)		(1.37)		(-2.63)		(0.95)
T.Burden x Non-Star		-0.007		-0.005		-0.031***		-0.021***
		(-1.05)		(-0.85)		(-4.74)		(-4.28)
1(Star)		0.042		-0.044*		-0.062*		-0.096***
		(1.38)		(-1.84)		(-1.70)		(-3.12)
Ln(Experience)	-0.070***	-0.075***	-0.119***	-0.115***	-0.021	-0.023	-0.098***	-0.094***
	(-4.23)	(-4.34)	(-13.10)	(-12.35)	(-1.26)	(-1.30)	(-10.40)	(-9.79)
Ln(Prior Prod.)	-0.033**	-0.025*	-0.088***	-0.092***	-0.075***	-0.064***	-0.104***	-0.103***
	(-2.30)	(-1.69)	(-15.16)	(-14.10)	(-4.54)	(-4.09)	(-12.40)	(-12.55)
Ln(Yr. Since Prev. Pat.)	-0.083***	-0.079***	0.007	0.005	-0.083***	-0.079***	0.012	0.011
	(-9.20)	(-8.69)	(0.97)	(0.70)	(-9.96)	(-9.94)	(1.57)	(1.54)
1(Indiv. Assignee)	0.027	0.027	-0.035	-0.035	-0.003	-0.003	0.009	0.009
	(0.46)	(0.45)	(-0.69)	(-0.68)	(-0.07)	(-0.06)	(0.16)	(0.17)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950
Star=Non-Star (p-value)		0.009		0.010		0.782		0.001
$\bar{y}$	4.796		2.195		4.884		2.377	
Star $\bar{y}$		12.709		2.272		12.060		2.514
Non-Star $\bar{y}$		3.789		2.184		3.964		2.355

Panel B: Text-based Impact (Poisson)

	New n-grams Reused (Scaled)				New n-grams Reused (Unscaled)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NnR	NnR	NnR/Patent	NnR/Patent	NnR	NnR	NnR/Patent	NnR/Patent
Time Burden	-0.012*		-0.002		-0.046***		-0.031***	
	(-1.82)		(-0.26)		(-6.07)		(-5.17)	
T.Burden x Star		-0.035***		0.005		-0.035**		-0.005
		(-3.03)		(0.45)		(-2.44)		(-0.44)
T.Burden x Non-Star		-0.005		-0.003		-0.050***		-0.035***
		(-0.78)		(-0.41)		(-5.70)		(-5.62)
1(Star)		0.057		-0.013		-0.119**		-0.117***
		(1.50)		(-0.43)		(-2.21)		(-2.72)
Ln(Experience)	-0.066***	-0.071***	-0.111***	-0.109***	-0.006	-0.006	-0.069**	-0.067**
	(-3.25)	(-3.37)	(-10.35)	(-9.72)	(-0.19)	(-0.20)	(-2.14)	(-2.09)
Ln(Prior Prod.)	-0.049***	-0.039**	-0.109***	-0.111***	-0.094***	-0.079***	-0.120***	-0.115***
	(-3.02)	(-2.36)	(-15.75)	(-14.46)	(-4.72)	(-4.42)	(-11.05)	(-11.35)
Ln(Yr. Since Prev. Pat.)	-0.092***	-0.088***	-0.003	-0.004	-0.101***	-0.095***	-0.001	0.000
	(-8.31)	(-8.15)	(-0.32)	(-0.45)	(-5.63)	(-5.71)	(-0.08)	(0.03)
1(Indiv. Assignee)	-0.019	-0.019	-0.100*	-0.100*	-0.059	-0.058	-0.037	-0.036
	(-0.27)	(-0.28)	(-1.65)	(-1.65)	(-1.05)	(-1.03)	(-0.64)	(-0.62)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950	4,527,950
Star=Non-Star (p-value)		0.012		0.400		0.361		0.020
$\bar{y}$	4.827		2.132		18.731		8.909	
Star $\bar{y}$		13.443		2.287		48.716		10.022
Non-Star $\bar{y}$		3.729		2.112		14.910		8.767

Table 6: **Breakthroughs, Defensive Patents, and Process Patenting**

The dependent variable are various measures of exploratory (breakthrough) characterization measures (Panel A) and various strategic (defensive/"exploitative") characterization measures (Panel B). The variables of interest are Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns are OLS specifications, except for Panel B Columns (5)-(6), which report Poisson Pseudo-Maximum Likelihood estimations.

Panel A: Exploratory Innovation (OLS)

	Sum RETech		RETech per Patent		1(Top RETech Decile Patent)		Technological Breadth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Burden	-0.059***		-0.006		-0.002**		-0.010***	
	(-4.89)		(-1.33)		(-2.56)		(-16.98)	
T.Burden x Star		-0.340***		0.001		-0.006***		-0.010***
		(-6.37)		(0.23)		(-4.98)		(-14.01)
T.Burden x Non-Star		-0.022		-0.007		-0.002*		-0.011***
		(-1.63)		(-1.45)		(-1.94)		(-17.03)
1(Star)		0.807***		-0.053***		0.011**		-0.004**
		(4.46)		(-3.00)		(2.29)		(-2.53)
Ln(Experience)	0.092**	0.051	-0.011***	-0.011***	0.000	-0.000	0.000	0.000
	(2.51)	(1.49)	(-3.21)	(-3.18)	(0.16)	(-0.22)	(0.58)	(0.76)
Ln(Prior Prod.)	0.055*	0.103***	-0.036***	-0.033***	-0.002**	-0.001*	-0.001***	-0.001**
	(1.65)	(3.31)	(-15.48)	(-15.07)	(-2.54)	(-1.83)	(-2.64)	(-2.22)
Ln(Yr. Since Prev. Pat.)	-0.084***	-0.061***	0.041***	0.042***	0.002*	0.002**	-0.002***	-0.002***
	(-6.73)	(-5.72)	(10.88)	(11.52)	(1.89)	(2.22)	(-3.92)	(-3.79)
1(Indiv. Assignee)	0.066	0.057	-0.035*	-0.034*	-0.001	-0.002	0.004	0.004
	(0.67)	(0.58)	(-1.91)	(-1.87)	(-0.20)	(-0.21)	(1.56)	(1.58)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,017,747	5,017,747	5,017,747	5,017,747	5,017,747	5,017,747	5,017,747	5,017,747
Adj. R-sq	0.38	0.38	0.58	0.58	0.30	0.30	0.80	0.80
Star=Non-Star (p-value)		0.000		0.112		0.001		0.025
$\bar{y}$	2.217		1.096		0.137		0.384	
Star $\bar{y}$		5.454		1.049		0.211		0.363
Non-Star $\bar{y}$		1.824		1.102		0.128		0.387

Panel B: Strategic Innovation

	Self-Cite Ratio		1(Defensive Patent)		Scaled Proc. Claims Per Patent		1(Process Patent)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Burden	0.001		0.000		0.004		0.001	
	(0.92)		(0.28)		(1.04)		(0.95)	
T.Burden x Star		-0.000		-0.010***		-0.004		-0.008***
		(-0.39)		(-4.53)		(-0.53)		(-4.16)
T.Burden x Non-Star		0.001		0.002		0.006		0.002**
		(1.19)		(1.31)		(1.35)		(1.97)
1(Star)		0.009***		0.046***		0.017		0.037***
		(3.41)		(7.53)		(1.01)		(6.75)
Ln(Experience)	0.002***	0.002***	0.013***	0.012***	-0.004	-0.005	0.005***	0.004***
	(2.76)	(2.62)	(8.46)	(7.78)	(-1.18)	(-1.62)	(3.85)	(3.15)
Ln(Prior Prod.)	0.013***	0.012***	0.035***	0.034***	-0.011***	-0.009***	0.004***	0.004***
	(22.71)	(22.45)	(26.15)	(26.43)	(-5.74)	(-4.33)	(2.89)	(2.79)
Ln(Yr. Since Prev. Pat.)	0.004***	0.003***	-0.005***	-0.005***	-0.005*	-0.003	-0.013***	-0.013***
	(8.02)	(7.46)	(-5.04)	(-5.06)	(-1.68)	(-1.29)	(-13.50)	(-13.28)
1(Indiv. Assignee)	0.003	0.003	0.004	0.004	0.024	0.024	0.011	0.011
	(0.82)	(0.78)	(0.49)	(0.41)	(0.88)	(0.87)	(1.00)	(0.96)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4,825,390	4,825,390	4,825,390	4,825,390	4,957,684	4,957,684	5,112,496	5,112,496
Adj. R-sq	0.35	0.35	0.33	0.33			0.32	0.32
Star=Non-Star (p-value)		0.083		0.000		0.050		0.000
$\bar{y}$	0.119		0.377		1.028		0.438	
Star $\bar{y}$		0.170		0.656		1.004		0.628
Non-Star $\bar{y}$		0.113		0.342		1.031		0.416

Table 7: **Inventor Mobility**

In Panel A, the dependent variable is an indicator for whether an inventor changes job. In Panel B, the dependent variables are indicators for moving to an employer with more inventors, moving internally, and moving internally to a location with more inventors. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns report OLS specifications. In Panel B, Columns (3) and (6) are conditional on, respectively, changing jobs and moving internally.

Panel A: Turnover Response

	1(Change Jobs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	0.003***	0.002***	0.002***	0.002***	0.002***	
	(4.40)	(4.87)	(4.73)	(4.58)	(5.24)	
T.Burden x Star						0.002*
						(1.82)
T.Burden x Non-Star						0.002***
						(5.09)
1(Star)						-0.000
						(-0.04)
Ln(Experience)					0.028***	0.028***
					(8.79)	(8.76)
Ln(Prior Prod.)					-0.006***	-0.006***
					(-8.31)	(-8.47)
Ln(Yr. Since Prev. Pat.)					-0.027***	-0.027***
					(-11.48)	(-11.39)
1(Indiv. Assignee)					-0.021	-0.021
					(-0.80)	(-0.80)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer FE	Yes	No	No	No	No	No
Year FE	Yes	No	No	No	No	No
Employer-by-Year FE	No	Yes	Yes	No	No	No
City FE	No	No	Yes	No	No	No
Employer-by-City-by-Year FE	No	No	No	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Adj. R-sq	0.11	0.20	0.20	0.22	0.22	0.22
Star=Non-Star (p-value)						0.872
$\bar{y}$	0.100	0.100	0.100	0.100	0.100	
Star $\bar{y}$						0.169
Non-Star $\bar{y}$						0.096

Panel B: Additional Mobility Analyses

	1(Move Larger Employer)			1(Move Internal)		1(Move Internal Larger)
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	0.002***			0.001***		
	(7.69)			(4.11)		
T.Burden x Star		0.001	0.013***		-0.002**	-0.003
		(0.81)	(3.01)		(-2.12)	(-1.22)
T.Burden x Non-Star		0.002***	0.016***		0.001***	0.002*
		(8.01)	(7.57)		(4.61)	(1.75)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	No	Yes	Yes	No
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	1,258,712	12,564,053	12,564,053	692,997
Adj. R-sq	0.27	0.27	0.45	0.14	0.14	0.57
Star=Non-Star (p-value)		0.284	0.321		0.000	0.036
$\bar{y}$	0.045			0.055		
Star $\bar{y}$		0.079	0.469		0.103	0.413
Non-Star $\bar{y}$		0.043	0.447		0.053	0.353

Table 8: **Inventor Teams**

The dependent variables are several measures of inventor team size, at the inventor-year level. The variables of interest are Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in the prior year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns in Panel A report Poisson Pseudo Maximum Likelihood estimations. Panel B reports OLS specifications. Panel B Column (3) analyzes Domestic Firm inventors and Column (4) analyzes Foreign Firm inventors.

Panel A: Total Team Size (Poisson)

	Coauthors					
	All Inventors		Domestic Firm		Foreign Firm	
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.010***		-0.008**		-0.010***	
	(-4.62)		(-2.40)		(-3.66)	
T.Burden x Star		-0.027***		-0.017***		-0.035***
		(-6.19)		(-2.99)		(-5.72)
T.Burden x Non-Star		-0.005**		-0.006		-0.004
		(-2.45)		(-1.47)		(-1.55)
1(Star)		0.079***		0.037*		0.109***
		(5.68)		(1.69)		(6.35)
Ln(Experience)	0.022***	0.019***	0.036***	0.034***	0.015**	0.011
	(3.99)	(3.33)	(4.39)	(4.18)	(1.97)	(1.33)
Ln(Prior Prod.)	0.069***	0.069***	0.058***	0.058***	0.071***	0.071***
	(12.64)	(12.27)	(4.99)	(5.10)	(12.70)	(11.75)
Ln(Yr. Since Prev. Pat.)	-0.033***	-0.033***	-0.030***	-0.030***	-0.037***	-0.037***
	(-11.05)	(-11.82)	(-8.91)	(-9.42)	(-7.74)	(-8.27)
1(Indiv. Assignee)	0.022	0.021	-0.008	-0.008	0.024	0.023
	(1.59)	(1.50)	(-0.26)	(-0.27)	(1.54)	(1.42)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,112,496	5,112,496	2,503,088	2,503,088	2,317,816	2,317,816
Star=Non-Star (p-value)		0.000		0.093		0.000
$\bar{y}$	4.4		4.6		4.4	
Star $\bar{y}$		8.9		9.0		8.8
Non-Star $\bar{y}$		3.9		4.1		3.8

Panel B: Within-Team Turnover

	New Coauthors / Total Coauthors			
	(1)	(2)	(3)	(4)
Time Burden	-0.002			
	(-1.44)			
T.Burden x Star		0.004***	0.006***	0.003
		(2.65)	(2.73)	(1.28)
T.Burden x Non-Star		-0.002*	-0.006***	-0.000
		(-1.90)	(-2.82)	(-0.21)
1(Star)		-0.003	-0.018***	0.002
		(-0.61)	(-2.71)	(0.30)
Ln(Experience)	-0.001	0.001	-0.013***	0.008***
	(-0.30)	(0.23)	(-3.37)	(2.94)
Ln(Prior Prod.)	-0.118***	-0.121***	-0.124***	-0.117***
	(-88.67)	(-88.23)	(-46.58)	(-63.72)
Ln(Yr. Since Prev. Pat.)	0.067***	0.066***	0.051***	0.077***
	(29.85)	(29.10)	(10.70)	(41.85)
1(Indiv. Assignee)	-0.017**	-0.018**	-0.010	-0.017*
	(-2.14)	(-2.15)	(-0.62)	(-1.84)
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	4,600,927	4,600,927	2,303,218	2,090,500
Adj. R-sq	0.36	0.36	0.37	0.35
Star=Non-Star (p-value)		0.000	0.000	0.126
$\bar{y}$	0.496			
Star $\bar{y}$		0.380	0.339	0.424
Non-Star $\bar{y}$		0.511	0.467	0.564

Table 9: **Time Burden Across Technology Class**

The dependent variables are inventor productivity, an inventor's scaled citations for patents filed in a productive year, and an indicator for whether an inventor changes job. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. Panel A reports results with the inclusion of Technology Class-by-Year FE. Panel B Columns (1)-(6) contain only inventors working in rapidly evolving technology classes, and Columns (7)-(12) contain inventors working in mature technology classes. Panel C excludes all Chemistry and Software inventors (Lerner and Seru (2021)).

Panel A: Technology Class-by-Year FE

	CPC Section-by-Year FE						CPC Class-by-Year FE					
	Patent Count		Scaled Citations		1(Change Jobs)		Patent Count		Scaled Citations		1(Change Jobs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time Burden	-0.021***		-0.015*		0.002***		-0.036***		-0.017**		0.002***	
	(-5.60)		(-1.84)		(4.85)		(-8.13)		(-2.10)		(3.86)	
T.Burden x Star		-0.151***		-0.029**		0.002*		-0.158***		-0.030***		0.002
		(-19.44)		(-2.40)		(1.74)		(-20.36)		(-2.59)		(1.49)
T.Burden x Non-Star		0.010***		-0.011		0.002***		-0.001		-0.012		0.002***
		(2.63)		(-1.32)		(4.74)		(-0.20)		(-1.50)		(3.82)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech. Class-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	5,112,496	5,112,496	12,564,053	12,564,053	12,564,053	12,564,053	5,112,496	5,112,496	12,564,053	12,564,053
Adj. R-sq					0.22	0.22					0.22	0.22
Star=Non-Star (p-value)		0.000		0.072		0.879		0.000		0.081		0.981
$\bar{y}$	0.815		1.333		0.100		0.815		1.333		0.100	
Star $\bar{y}$		4.376		4.103		0.169		4.376		4.103		0.169
Non-Star $\bar{y}$		0.619		1.001		0.096		0.619		1.001		0.096

Panel B: Stability of Technology Classes

	Rapidly Evolving Tech. Class						Stable Tech. Class					
	Patent Count		Scaled Citations		1(Change Jobs)		Patent Count		Scaled Citations		1(Change Jobs)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time Burden	-0.023**		-0.056***		0.002		-0.021***		-0.002		0.001***	
	(-2.27)		(-3.25)		(1.41)		(-5.68)		(-0.23)		(2.76)	
T.Burden x Star		-0.134***		-0.061***		-0.000		-0.151***		-0.017		0.003**
		(-9.23)		(-3.00)		(-0.02)		(-15.06)		(-1.20)		(2.34)
T.Burden x Non-Star		0.009		-0.056***		0.002		0.011***		0.003		0.001**
		(1.10)		(-2.99)		(1.48)		(2.63)		(0.34)		(2.40)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3,491,046	3,491,046	1,464,066	1,464,066	3,491,046	3,491,046	9,073,004	9,073,004	3,648,428	3,648,428	9,073,004	9,073,004
Adj. R-sq					0.25	0.25					0.23	0.23
Star=Non-Star (p-value)		0.000		0.772		0.286		0.000		0.126		0.163
$\bar{y}$	0.884		1.375		0.104		0.788		1.316		0.099	
Star $\bar{y}$		4.698		4.039		0.161		4.234		4.131		0.172
Non-Star $\bar{y}$		0.652		1.029		0.100		0.606		0.990		0.095

Panel C: Exclude Chemistry and Software

	Patent Count		Scaled Citations		1(Change Jobs)	
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.024***		-0.012		0.001***	
	(-6.96)		(-1.45)		(3.12)	
T.Burden x Star		-0.151***		-0.024*		0.003*
		(-17.92)		(-1.76)		(1.76)
T.Burden x Non-Star		0.008**		-0.009		0.001***
		(2.26)		(-1.04)		(2.85)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9,437,754	9,437,754	3,813,745	3,813,745	9,437,754	9,437,754
Adj. R-sq					0.22	0.22
Star=Non-Star (p-value)		0.000		0.159		0.380
$\bar{y}$	0.819		1.368		0.101	
Star $\bar{y}$		4.486		4.188		0.179
Non-Star $\bar{y}$		0.614		1.018		0.097

Table 10: **Alternative Star Inventor Definitions**

The dependent variables are inventor productivity, an inventor's scaled citations for patents filed in a productive year, and an indicator for whether an inventor changes job. The variable of interest is Time Burden and its interactions. The percentile split used to define "Star" is indicated in column headers. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized.

Panel A: Inventor Productivity

	Patent Count					
	(1) 90^{th} Prod.	(2) 95^{th} Prod.	(3) 99^{th} Prod.	(4) 90^{th} Cites	(5) 95^{th} Cites	(6) 99^{th} Cites
T.Burden x Star	-0.146***	-0.150***	-0.149***	-0.135***	-0.139***	-0.131***
	(-20.34)	(-19.80)	(-13.99)	(-18.98)	(-18.23)	(-10.24)
T.Burden x Non-Star	0.028***	0.011***	-0.009***	0.018***	0.002	-0.013***
	(6.98)	(2.87)	(-2.60)	(4.25)	(0.61)	(-3.73)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Star=Non-Star (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
Star $\bar{y}$	3.184	4.376	8.748	2.629	3.493	6.312
Non-Star $\bar{y}$	0.542	0.619	0.729	0.593	0.660	0.754

Panel B: Scaled Citations

	Cites					
	(1) 90^{th} Prod.	(2) 95^{th} Prod.	(3) 99^{th} Prod.	(4) 90^{th} Cites	(5) 95^{th} Cites	(6) 99^{th} Cites
T.Burden x Star	-0.031***	-0.028**	-0.020	-0.077***	-0.080***	-0.074***
	(-2.95)	(-2.38)	(-1.10)	(-6.50)	(-5.70)	(-4.40)
T.Burden x Non-Star	-0.006	-0.011	-0.014*	0.029***	0.012	-0.007
	(-0.79)	(-1.32)	(-1.82)	(3.10)	(1.33)	(-0.83)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496
Star=Non-Star (p-value)	0.007	0.079	0.692	0.000	0.000	0.000
Star $\bar{y}$	3.134	4.103	7.659	4.481	6.386	14.178
Non-Star $\bar{y}$	0.889	1.001	1.178	0.596	0.755	1.031

Panel C: Inventor Mobility

	1(Change Jobs)					
	(1) 90^{th} Prod.	(2) 95^{th} Prod.	(3) 99^{th} Prod.	(4) 90^{th} Cites	(5) 95^{th} Cites	(6) 99^{th} Cites
T.Burden x Star	0.002**	0.002*	0.005**	0.002**	0.003**	0.003
	(2.08)	(1.82)	(2.40)	(2.33)	(2.42)	(1.14)
T.Burden x Non-Star	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.02)	(5.09)	(5.08)	(5.09)	(5.05)	(5.19)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Adj. R-sq	0.22	0.22	0.22	0.22	0.22	0.22
Star=Non-Star (p-value)	0.851	0.872	0.128	0.839	0.545	0.798
Star $\bar{y}$	0.160	0.169	0.176	0.143	0.147	0.143
Non-Star $\bar{y}$	0.093	0.096	0.099	0.095	0.097	0.100

Table 11: **Inventors With Greater Compliance Support**

The dependent variables are inventor productivity, an inventor's scaled citations for patents filed in a productive year, and an indicator for whether an inventor changes job. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), the number of years since last patent was filed (logged), inventor productivity over the previous 5 years (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized.

U.S. Publicly Traded Firms

	Patent Count		Scaled Citations		1(Change Jobs)	
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.020**		-0.005		0.001**	
	(-2.05)		(-0.32)		(2.41)	
T.Burden x Star		-0.124***		-0.023		0.002**
		(-8.33)		(-1.25)		(2.54)
T.Burden x Non-Star		0.012		0.001		0.001**
		(1.22)		(0.07)		(2.17)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,893,800	2,893,800	1,282,542	1,282,542	2,893,800	2,893,800
Adj. R-sq					0.44	0.44
Star=Non-Star (p-value)		0.000		0.140		0.225
$\bar{y}$	0.994		1.903		0.069	
Star $\bar{y}$		4.739		5.465		0.088
Non-Star $\bar{y}$		0.705		1.336		0.068

Table 12: **Addressing Known Issues in Patent Data**

The dependent variables are inventor productivity and an inventor's scaled citations for patents filed in a productive year. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), the number of years since last patent was filed (logged), inventor productivity over the previous 5 years (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized.

Panel A: Reduced Sample (1993 - 2014)

	Patent Count		Scaled Citations	
	(1)	(2)	(3)	(4)
Time Burden	-0.020***		-0.017**	
	(-4.54)		(-2.05)	
T.Burden x Star		-0.149***		-0.035***
		(-18.55)		(-2.74)
T.Burden x Non-Star		0.009**		-0.012
		(2.00)		(-1.39)
Controls / 1(Star)	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	10,148,672	10,148,672	3,601,088	3,601,088
Star=Non-Star (p-value)		0.000		0.029
$\bar{y}$	0.704		1.643	
Star $\bar{y}$		3.948		4.451
Non-Star $\bar{y}$		0.524		1.260

Panel B: Excluding California & Massachusetts

	Patent Count		Scaled Citations	
	(1)	(2)	(3)	(4)
Time Burden	-0.019***		-0.015*	
	(-4.79)		(-1.66)	
T.Burden x Star		-0.151***		-0.031**
		(-19.14)		(-2.28)
T.Burden x Non-Star		0.011***		-0.010
		(2.70)		(-1.11)
Controls / 1(Star)	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	10,757,718	10,757,718	4,325,554	4,325,554
Star=Non-Star (p-value)		0.000		0.074
$\bar{y}$	0.795		1.202	
Star $\bar{y}$		4.304		3.721
Non-Star $\bar{y}$		0.608		0.909

Table 13: **Clustered Standard Errors**

The dependent variables are inventor productivity, an inventor's scaled citations for patents filed in a productive year, and an indicator for whether an inventor changes job. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered as indicated in column headers. All independent variables are lagged. All continuous independent variables are standardized.

Alternative Clustering

	Patent Count			Cites Scaled			1(Change Jobs)		
	(1) Inv.	(2) Inv. & Asgn.-Year	(3) Inv. & Asgn.	(4) Inv.	(5) Inv. & Asgn.-Year	(6) Inv. & Asgn.	(7) Inv.	(8) Inv. & Asgn.-Year	(9) Inv. & Asgn.
T.Burden x Star	-0.150***	-0.150***	-0.150***	-0.028***	-0.028***	-0.028**	0.002***	0.002**	0.002*
	(-33.18)	(-26.21)	(-19.80)	(-3.48)	(-2.95)	(-2.38)	(2.66)	(2.38)	(1.82)
T.Burden x Non-Star	0.011***	0.011***	0.011***	-0.011*	-0.011	-0.011	0.002***	0.002***	0.002***
	(3.86)	(3.38)	(2.87)	(-1.83)	(-1.60)	(-1.32)	(5.53)	(5.27)	(5.09)
1(Star)	0.542***	0.542***	0.542***	-0.005	-0.005	-0.005	-0.000	-0.000	-0.000
	(40.97)	(28.51)	(21.26)	(-0.23)	(-0.19)	(-0.16)	(-0.07)	(-0.06)	(-0.04)
Ln(Experience)	0.168***	0.168***	0.168***	-0.027***	-0.027***	-0.027**	0.028***	0.028***	0.028***
	(55.98)	(36.15)	(24.82)	(-3.96)	(-3.40)	(-2.50)	(70.58)	(31.86)	(8.76)
Ln(Prior Prod.)				0.031***	0.031***	0.031***	-0.006***	-0.006***	-0.006***
				(7.91)	(5.64)	(2.96)	(-21.96)	(-16.74)	(-8.47)
Ln(Yr. Since Prev. Pat.)	-0.035***	-0.035***	-0.035**	-0.076***	-0.076***	-0.076***	-0.027***	-0.027***	-0.027***
	(-25.79)	(-9.68)	(-2.48)	(-20.57)	(-17.00)	(-12.17)	(-113.33)	(-45.98)	(-11.39)
1(Indiv. Assignee)	-0.003	-0.003	-0.003	-0.010	-0.010	-0.010	-0.021***	-0.021***	-0.021
	(-0.15)	(-0.12)	(-0.05)	(-0.33)	(-0.29)	(-0.30)	(-5.85)	(-3.06)	(-0.80)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	5,112,496	5,112,496	5,112,496	12,564,053	12,564,053	12,564,053
Adj. R-sq							0.22	0.22	0.22
Star=Non-Star (p-value)	0.000	0.000	0.000	0.006	0.024	0.079	0.797	0.822	0.872
Star $\bar{y}$	4.376	4.376	4.376	4.103	4.103	4.103	0.169	0.169	0.169
Non-Star $\bar{y}$	0.619	0.619	0.619	1.001	1.001	1.001	0.096	0.096	0.096

Internet Appendix

A Alternative Burden Estimation Decisions

A.1 Correlations across patent estimates

In the main text (Section 5.1), I describe the procedure for creating patent-level burden estimates with the equation:

$$\text{Patent Burden}_{p,f} = \sum_{k} (\theta_{k,p} \cdot \text{Topic Burden}_{k,f})$$

where $\theta_{k,p}$ represents the topic proportion of a patent, k represents topic, p represents patent, and f is the year of the patent's filing. $\theta_{k,p}$ is the residualized topic burden, meaning the mean of a topic across patents is subtracted from each patent's distribution. Topics comprising less than 1% of a patent are then set to zero, and the sum-product is computed. This procedure is meant to minimize noise, making 'common' or 'general' topics less influential in the construction of burden, and set a lower bound on what topics are actually relevant to a given patent.

However, because these choices are supervised, I vary them to show how they influence patent burden estimates. In Table A2, I report correlations between the estimates used in the main text, and several variations. First, 'Time (Unresid.)' uses the topic distributions directly from the model. It is 98.1% correlated with the primary measure. Setting topics less than 1% and 5% to zero, without residualizing, also produces highly correlated patent burden estimates, at 99.5% and 90.3% correlated.

A.2 Correlations across inventor estimates

The correlations from the previous section show that techniques addressing noise in the patent burden estimates change the output minutely. The next aggregation decision involves creating Technology Class estimates over time. In the main text, I use the median patent in a technology class-year (CPC Class) and the median of an inventor's relevant technology classes, holding classes relevant for 4 years. In Table A3, I report correlations across measures using the patent burdens above aggregated to the technology class using the median or mean, CPC

Class or CPC Sub-class (a more granular classification), and holding relevant for 3 or 4 years.

Varying aggregation decisions produces highly correlated estimates. Using raw, residualized, or zeroed patent burdens aggregated to the CPC Class level ("CPC3") and holding these Classes relevant to an inventor for 3 or 4 years produces estimates with greater than 90% correlations with the measured used in the main text (reported in Column 1 of Table A3). Aggregating patent burdens instead to the more granular CPC Sub-class produces correlations between 0.78 and 0.83.

A.3 Variance Decomposition

In Table A5, I report variance decompositions for the measure used in the main text (Time Burden (CPC3)) and the variant constructed from CPC Sub-classes (Time Burden (CPC4)). I regress each measure on fixed effects of varying stringency and report the R-squared from each regression.

Examining Column (1), time-invariant employer characteristics explain approximately one-third (36.1%) of the variation in Time Burden (CPC3). An additional 30.3% is explained by macroeconomic conditions. This means that approximately one-third (32.5%) of the overall variation in Time Burden (CPC3) occurs at the inventor-level. This can then be separated into a time-invariant inventor-specific component (20.5%) and a time-varying inventor-specific component (12%). In Columns (2), I replace employer with broad groupings of technology, to compare the magnitude of variation explained by field to that explained by employer. CPC Section explains less variation than Employer (22.7%), while CPC Class explains more (39.2%). This is to be expected, as the measure is constructed from CPC Classes; an inventor who works primarily in 1 CPC Class will have nearly all of Time Burden explained by these fixed effects. I find similar relations when swapping Time Burden (CPC3) for Time Burden (CPC4). The inventor-level variation is 47-208% larger when Time Burden is constructed at the CPC Sub-class level, which is expected as the technology classifications are more granular. A cost of this granularity is that there are more years where a technology sub-class has zero patents filed and thus a burden cannot be estimated, though results using these more granular measures are quite similar (reported in next sub-section).

A.4 Regressions across inventor estimates

In Table A4, I report and discuss productivity regressions for the inventor-level measures. I interact each measure with a Star indicator and include all controls, inventor fixed effects, and Employer-by-City-by-Year FE. The coefficients for various Time Burden measures interacted with Star range between -0.125 and -0.187, all highly statistically significant. The measure used in the main text generates a coefficient of -0.15, similar to the mean and median of these estimates, at -0.154 and -0.151, respectively. I also report the estimate for Paperwork Burden interacted with a Star indicator (column header 'PW'), though this is likely a noisier proxy for an inventor's actual burden. The coefficient is -0.053 and highly statistically significant. Non-Star coefficients vary considerably more, from statistically insignificant 0.8% declines to statistically significant increases of 5.6%. Given Non-Stars low productivity, these increases represent small increases in absolute terms (e.g. a 5.6% increase is 0.035 more patents per year). These higher coefficients for Non-Stars occur when patent burdens are aggregated using means instead of medians.

B Alternative Productivity Measures

B.1 Citation-weighted Patents

Patents extend scientific knowledge, but they are also legal monopolies in product markets. This latter factor yields strategic value to the patent holder, but may not necessarily be correlated with extending scientific knowledge. For instance, process patents are quite valuable to firms, but do not necessarily receive many citations, as they primarily build on firms' internal knowledge (Bena et al. (2021), Bena et al. (2022), Khetan and Nain (2023)). Patent citations are also known for having other issues which may complicate the 'more citations means a better invention', like strategic citing (Lampe (2012)), patent examiner busyness and expertise (Righi and Simcoe (2019), Lei and Wright (2017)), and changing citation practices (Kuhn et al. (2020)). In the main text, I use the count of patents filed and granted as a measure of productivity. However, this measure counts a patent which extends scientific knowledge similarly to

patents that 'only' convey legal power. The measure 'citation-weighted patents' values only the innovations that advance scientific knowledge (at least as measured by citations), and is calculated as:

$$\text{Citation-weighted Patents}_{i,t} = \sum_{j \in p_{i,t}} c_{i,j}$$

where i represents inventor, t represents year, j represents patent, $p_{i,t}$ represents the patents filed by an inventor i in year t, and $c_{i,j}$ represents the scaled citations of a given patent. This measure perceives a patent with zero citations as zero production, and measures more directly the scientific frontier advancement. A patent's citations in the above measure are scaled by the mean of accrued citations by patents filed for in that year and technology class, to adjust for technological differences and truncation bias. Higher values indicate greater value relative to that field at a given time.

I use citation-weighted patents as the dependent variable in Table A6 Panel A. I report my most stringent specification for brevity, and find that a 1 standard deviation increase in Time Burden is associated with a 1.8% decline in citation-weighted patent output. In Column (2), I interact Time Burden with an indicator for Star, and find the result is again concentrated in Stars. A 1 standard deviation increase in Time Burden is associated with a 10.5% reduction in the citation-weighted patent output of Star Inventors. This result supports the notion that not only are Star Inventors producing fewer patents, they are also contributing less to scientific advancement as regulatory burden rises. The effect in Non-Stars is statistically and economically insignificant. I repeat these two specifications and truncate the sample at 2014 and find similar results. Given a 1 standard deviation increase in Time Burden, Stars experience an 11.2% reduction in citation-weighted patent output, and Non-Stars experience a statistically insignificant 0.5% increase for the same increase in burden.

B.2 Coauthor-weighted Patents

Patents often have multiple inventors. Prior literature has attributed patents to inventors in fractions, e.g. if two inventors are listed on a patent, and that is their only innovation year, each receives a productivity measure of 0.5. I calculate an inventor's 'coauthor-weighted

patents' as:

$$\text{Coauthor-weighted Patents}_{i,t} = \sum_{j \in p_{i,t}} \frac{1}{n_j}$$

where i represents inventor, t represents year, j represents patent, $p_{i,t}$ represents the patents filed by an inventor i in year t, and n_j represents the number of inventors listed on patent j.

I use citation-weighted patents as the dependent variable in Table A6 Panel B. I report only my most stringent specification. The results are comparable to those in the main text. A 1 standard deviation increase in Time Burden is associated with a 1.6% decline in coauthor-weighted patent output. In Column (2), I interact Time Burden with an indicator for Star, and find the decline is concentrated in Star Inventors. A 1 standard deviation increase in Time Burden is associated with a 14% reduction in the coauthor-weighted patent output of Star Inventors. Similarly to the main text, Non-Stars a statistically significant increase of 1.4%. I then repeat these analyses in Columns (3) and (4) using a sample ending in 2014. The results are quantitatively similar. In terms of patents, this reduction is equivalent to about 5,600 fewer patents[1]. This figure assumes that Stars and Non-Stars on the same patent contribute equally, which may be a strong assumption, and so constitutes a lower bound on the decline in Star patenting.

C Non-Residence-based Specifications

Inventors are required to report their residence on patent applications, and this residence is recorded in the USPTO-Patentsview data. In my primary analyses, I include Employer-by-City-by-Year fixed effects to absorb both time-varying employer and time-varying location characteristics, with the latter containing factors like 'high tech clusters' (Moretti (2021)) and other placed-based incentives. However, there may be a concern that these fixed effects remove interesting variation, and that it would be preferable to compare inventors working for the same employer in the same primary technology class instead, rather than inventors who simply work for the same employer in the same city.

In Table A7, I report these alternative specifications. Inference is similar to my primary

1. There are, on average, 24,644 Star Inventors each year with an average annual productivity of 1.634 patents. Exponentiating the coefficient, $1 - e^{-0.151} = 0.14$. So, 24,644 x 1.634 x 0.14 = 5,637 patents.

analyses. Using the most stringent alternative specification, requiring that an inventor work in the same primary technology classification for the same employer at the same time, a 1 standard deviation increase in Time Burden is associated with a 14.4% decline in Star output, similar to the 13.9% decline in the main text and statistically significant at the 1% level. I find no effect on Non-Stars. For the same increase in Time Burden, Stars also exhibit 2.4% lower scaled citations, compared to 2.8% in the main text, statistically significant at the 5% level. Non-Stars exhibit a statistically significant 1.8% lower scaled citations, compared to an insignificant 1.1% decline in the main text. Finally, I find similarly increased mobility in this new most stringent specification, but the effect is only significant in Non-Stars. The magnitude is the same as in the main text, approximately 2.1% increase in likelihood of turnover, or 0.2pp.

Table A1: **Description of Variables**

Variable	Description
Patent Count	The count of utility patents filed by an inventor in a given year. Patents with multiple inventors count as '1' for each inventor listed on the patent. Source: Patentsview.
Cites (Scaled)	A patent's raw citations (from other utility patents) are scaled by the average number of citations received by utility patents in that patent's technology class and filing year. These scaled values are then aggregated to the inventor-filing year. This scaling and aggregation method follows recommendations by Lerner and Seru (2021). Source: Patentsview.
Cites (Scaled) / Patent	Cites (Scaled) divided by the number of patents an inventor filed that year. Source: Patentsview.
Cites (Unscaled)	The count of raw citations to patents filed by an inventor in a given year, from other utility patents. Source: Patentsview.
Cites (Unscaled) / Patent	Cites (Unscaled) divided by the number of patents an inventor filed that year. Source: Patentsview.
Generality	One minus the Herfindahl concentration index of the number of patents citing across technology classes, and correcting for bias arising from cases with a small number of patents within technology classes. Source: Patentsview.
Originality	One minus the Herfindahl concentration index of the number of cited patents across technology classes, and correcting for bias arising from cases with a small number of patents within technology classes. Source: Patentsview.
New n-grams (Scaled)	The number of new n-grams (sum of words, bigrams, and trigrams) introduced to the patent corpus by a patent filed in a given year, scaled by the average number of new n-grams introduced by patents in that technology class and filing year. These scaled values are then aggregated to the inventor-filing year. Source: Arts et al. (2021).
New n-grams (Scaled) / Patent	New n-grams (Scaled) divided by the number of patents an inventor filed that year. Source: Arts et al. (2021).
New n-grams (Unscaled)	The number of new n-grams (sum of words, bigrams, and trigrams) introduced to the patent corpus by an inventor's patents filed in a given year. Source: Arts et al. (2021).
New n-grams (Unscaled) / Patent	New n-grams (Unscaled) divided by the number of patents an inventor filed that year. Source: Arts et al. (2021).

Variable	Description
New n-gram Reuse (Scaled)	The number of times the new n-grams introduced by a patent appeared in other patents over the following 5 years, scaled by average reuse of that patent's technology class and filing year. These scaled values are then aggregated to the inventor-filing year. Source: Arts et al. (2021).
New n-gram Reuse (Scaled) / Patent	New n-gram Reuse (Scaled) divided by the number of patent an inventor filed that year. Source: Arts et al. (2021).
New n-gram Reuse (Unscaled)	The number of times the new n-grams introduced by an inventor's patents appeared in other patents over the 5 years following the filing year. Source: Arts et al. (2021).
New n-gram Reuse (Unscaled) / Patent	New n-gram Reuse (Unscaled) divided by the number of patent an inventor filed that year. Source: Arts et al. (2021).
Sum(RETech)	The sum of patent RETech values, aggregated to the inventor-year level. Source: Bowen et al. (2022).
RETech per Patent	The Sum(RETech) divided by the number of patents an inventor filed in a year. Source: Bowen et al. (2022).
1(Top RETech Decile Patent)	An indicator for whether an inventor filed for a patent in the top decile of RETech in that filing year. Source: Bowen et al. (2022).
Technological Breadth	One minus the technological concentration of a patent's specialized vocabulary across the 6 NBER Technology Classifications. These values are averaged to the inventor-year level. Source: Bowen et al. (2022).
Self-Cite Ratio	A patent's self-cite ratio is the fraction of its backwards citations which cite the assignee's patent portfolio. These fractions are then averaged at the inventor-year level. Source: Patentsview.
1(Defensive Patent)	An indicator for whether an inventor created a patent with above average self-cite ratio relative to the patent's technology class and filing year. Source: Patentsview.
Scaled Process Claims / Patent	A patent's process claims are claims which discuss improvements in firm processes and methods. The count of a patent's process claims is scaled by the average number of process claims in that patent's technology class and filing year. These scaled values are then aggregated to the inventor-filing year. Source: Bena et al. (2022).
1(Process Patent)	An indicator for whether an inventor creates at least 1 patent with above average fraction of process claims relative to that patent's technology class and filing year. Source: Bena et al. (2022).
1(Change Job)	An indicator equal to one when an inventor's primary assignee (employer) differs from the previous year.
1(U.S.-based Inventor)	An indicator equal to one if the inventor resides in the United States. Source: Patentsview.

Variable	Description
1(U.S. Firm)	An indicator equal to one if the inventor works for an assignee designated as a domestic entity. Source: Patentsview.
1(Foreign Firm)	An indicator equal to one if the inventor works for an assignee designated as a foreign entity. Source: Patentsview.
1(Self-Employed)	An indicator equal to one if the inventor has a missing assignee or has only an individual assignee designation (Marx et al. (2009)). Source: Patentsview.
1(University)	An indicator equal to one if the inventor works for a university, as indicated by Ewens and Marx (2023).
1(Government)	An indicator equal to one if the inventor works for a government (domestic or foreign). Source: Patentsview.
Time Burden	An estimate of the time an inventor spends on compliance paperwork.
Paperwork Burden	An estimate of the number of times an inventor engages with regulators for compliance paperwork purposes.
Ln(Experience)	The natural log of years since the inventor's first patent.
Ln(Prior Productivity)	The natural log of 1 plus the previous 5 years of an inventor's patent output (Marx et al. (2015)).
Ln(Years Since Prev. Patent)	The natural log of 1 plus the number of years since the inventor's most recent patent.
1(Individual Assignee)	Whether the inventor received an individual assignee designation in a given year. Source: Patentsview.

Table A2: **Correlations Between Patent-level Time Burden Estimates**

This table reports pairwise correlations between several alternative estimations of patent-level burdens, and varies the noise-reduction steps taken ex ante. "Time (Resid.)" is the patent burden estimate used in this paper, constructed from residualized topic proportions and setting topics comprising less than 1% of a patent to zero. "Time (Unresid.)" uses the raw topic proportions. "Time (Unresid. Z1)" uses raw topic proportions and sets topics comprising less than 1% of a patent to zero. "Time (Unresid. Z5)" uses raw topic proportions and sets topics comprising less than 5% of a patent to zero. All alternative measures are at least 90% correlated with "Time (Resid.)". All correlations are highly statistically significant.

Correlation Table

	Time (Resid.)	Time (Unresid.)	Time (Unresid. Z1)	Time (Unresid. Z5)
Time (Resid.)	1			
Time (Unresid.)	0.981***	1		
Time (Unresid. Z1)	0.995***	0.989***	1	
Time (Unresid. Z5)	0.903***	0.872***	0.889***	1

Table A3: **Correlations Between Inventor-level Time Burden Estimates**

This table reports pairwise correlations between several alternative aggregations of patent burdens to the inventor-year level. "Mdn" indicates that the median patent burden represents the technology class burden and the median of an inventor's relevant classes represents inventor burden. "Resid." indicates that the topic proportions are residualized. "All" indicates that the topic proportions are unresidualized. "Z1" indicates that the topic proportions are unresidualized, but that topics comprising less than 1% of a patent are set to zero. "Z5" indicates that the topic proportions are unresidualized, but that topics comprising less than 5% of a patent are set to zero. "Mean" indicates that the average patent burden represents the technology class burden and the average of an inventor's relevant classes represents inventor burden. CPC3 and CPC4 indicate, respectively, that the measure was constructed using an inventor's CPC Class and CPC Sub-class history. "3yr" and "4yr" indicate for how long a class remains relevant to an inventor after the first time they patent in that class.

Correlation Table

	Mdn Resid. CPC3 4yr	Mdn All CPC3 4yr	Mdn Z1 CPC3 4yr	Mdn Z5 CPC3 4yr	Mean All CPC3 4yr	Mdn Resid. CPC3 3yr	Mdn All CPC3 3yr	Mean All CPC3 3yr	Mdn. Resid. CPC4 4yr	Mdn All CPC4 4yr
Mdn Resid. CPC3 4yr	1									
Mdn All CPC3 4yr	0.964***	1								
Mdn Z1 CPC3 4yr	0.995***	0.982***	1							
Mdn Z5 CPC3 4yr	0.965***	0.909***	0.950***	1						
Mdn Resid. CPC3 3yr	0.991***	0.956***	0.986***	0.956***	1					
Mdn All CPC3 3yr	0.959***	0.995***	0.977***	0.904***	0.964***	1				
Mean All CPC3 4yr	0.960***	0.996***	0.978***	0.906***	0.954***	0.992***	1			
Mdn. Resid. CPC4 4yr	0.783***	0.747***	0.776***	0.760***	0.776***	0.743***	0.745***	1		
Mdn All CPC4 4yr	0.835***	0.857***	0.847***	0.790***	0.828***	0.853***	0.855***	0.963***	1	
Mean All CPC4 4yr	0.832***	0.853***	0.843***	0.788***	0.826***	0.849***	0.856***	0.953***	0.989***	1

Table A4: **Regressions across inventor estimates**

The dependent variable is the inventor-level count of patents produced. The variables of interest are different measures of Regulatory Burden and their interactions with a Star indicator. Control variables are inventor experience (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns report Poisson Pseudo Maximum Likelihood estimations. All abbreviations are the same as the previous table, save for "PW", which refers to "Paperwork Burden".

Alternative Burden Measures

	CPC Class - 4 Year						CPC Class - 3 Year			CPC Sub-Class - 4 Year		
	Mdn Resid	Mdn All	Mdn Z1	Mdn Z5	Mean All	PW	Mdn Resid	Mdn All	Mean All	Mdn Resid	Mdn All	Mean All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
T.Burden x Star	-0.150***	-0.179***	-0.158***	-0.140***	-0.131***	-0.053***	-0.151***	-0.181***	-0.125***	-0.154***	-0.187***	-0.142***
	(-19.80)	(-22.97)	(-21.23)	(-18.35)	(-14.98)	(-8.83)	(-19.80)	(-22.78)	(-14.23)	(-17.70)	(-23.29)	(-17.52)
T.Burden x Non-Star	0.011***	0.013**	0.015***	0.013***	0.054***	-0.008	0.009**	0.010**	0.056***	0.000	0.002	0.030***
	(2.87)	(2.57)	(3.68)	(3.55)	(9.95)	(-1.60)	(2.52)	(2.04)	(10.62)	(0.01)	(0.39)	(6.80)
1(Star)	0.542***	0.813***	0.639***	0.482***	0.792***	0.053***	0.537***	0.810***	0.780***	0.403***	0.691***	0.636***
	(21.26)	(28.07)	(23.83)	(19.37)	(26.90)	(3.95)	(21.27)	(28.13)	(26.67)	(15.26)	(24.20)	(23.21)
Ln(Experience)	0.168***	0.159***	0.165***	0.169***	0.161***	0.185***	0.168***	0.159***	0.161***	0.173***	0.163***	0.165***
	(24.82)	(23.54)	(24.44)	(25.05)	(23.83)	(26.51)	(24.88)	(23.60)	(23.96)	(25.64)	(24.48)	(24.73)
Ln(Yr. Since Prev. Pat.)	-0.035**	-0.034**	-0.035**	-0.036**	-0.034**	-0.038***	-0.034**	-0.032**	-0.033**	-0.035**	-0.033**	-0.034**
	(-2.48)	(-2.36)	(-2.44)	(-2.50)	(-2.38)	(-2.66)	(-2.38)	(-2.27)	(-2.29)	(-2.47)	(-2.34)	(-2.37)
1(Indiv. Assignee)	-0.003	-0.004	-0.003	-0.002	-0.002	0.006	-0.003	-0.005	-0.002	-0.000	-0.003	-0.001
	(-0.05)	(-0.08)	(-0.06)	(-0.04)	(-0.04)	(0.13)	(-0.06)	(-0.10)	(-0.04)	(-0.00)	(-0.06)	(-0.02)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,521,816	12,521,816	12,521,816	12,516,546	12,516,546	12,516,546
Star=Non-Star (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Star $\bar{y}$	4.376	4.376	4.376	4.376	4.376	4.376	4.377	4.377	4.377	4.376	4.376	4.376
Non-Star $\bar{y}$	0.619	0.619	0.619	0.619	0.619	0.619	0.621	0.621	0.621	0.621	0.621	0.621

Table A5: **Variance Decomposition of Time Burden**

This table reports the R-squared of Time Burden calculated at the CPC Class (CPC3) and CPC Sub-class (CPC4) level regressed on varying fixed effects. The column header denotes the measure used for the dependent variable, and the column sub-header denotes the 'group'. 'Employer' refers to the assignee I identify as an inventor's employer. 'CPC Section' refers to the primary CPC Section an inventor patents in most often.

Variance Decomposition

Outcome:	Time Burden (CPC3)			Time Burden (CPC4)		
Group:	Employer	CPC Section	CPC Class	Employer	CPC Section	CPC Class
Group FE	36.1%	22.7%	39.2%	32.0%	15.8%	29.8%
Year FE	30.3%	43.8%	44.2%	19.0%	27.2%	27.6%
Group-by-Year FE	1.1%	1.0%	3.8%	1.2%	0.6%	3.2%
Subtotal:	67.5%	67.5%	87.2%	52.2%	43.6%	60.6%
Inventor-level (one minus subtotal)	32.5%	32.5%	12.8%	47.8%	56.4%	39.4%
Time-invariant (inventor FE)	20.5%	20.4%	5.4%	33.8%	23.9%	23.2%
Inventor-specific variation (residual)	12.0%	12.1%	7.4%	18.4%	19.7%	16.2%

Table A6: **Alternative Productivity Measures**

The dependent variable is inventor-level citation-weighted patent output in Panel A, and coauthor-weighted patent output in Panel B. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized. All columns report Poisson Pseudo Maximum Likelihood estimations.

Panel A: Citation-weighted Patents

	Full Sample		1993-2014	
	(1)	(2)	(3)	(4)
Time Burden	-0.018**		-0.017*	
	(-2.11)		(-1.95)	
T.Burden x Star		-0.111***		-0.119***
		(-7.88)		(-7.85)
T.Burden x Non-Star		0.005		0.007
		(0.61)		(0.81)
1(Star)		0.287***		0.277***
		(8.06)		(7.65)
Ln(Experience)	0.070***	0.069***	0.051***	0.049***
	(6.19)	(6.31)	(4.53)	(4.36)
Ln(Yr. Since Prev. Pat.)	-0.040***	-0.043***	-0.009	-0.012
	(-2.87)	(-3.11)	(-0.63)	(-0.91)
1(Indiv. Assignee)	-0.004	-0.006	-0.010	-0.013
	(-0.07)	(-0.11)	(-0.20)	(-0.25)
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	10,148,672	10,148,672
Star=Non-Star (p-value)		0.000		0.000
$\bar{y}$	0.543		0.583	
Star $\bar{y}$		3.430		3.621
Non-Star $\bar{y}$		0.384		0.415

Panel B: Coauthor-weighted Patents

	Full Sample		1993-2014	
	(1)	(2)	(3)	(4)
Time Burden	-0.016***		-0.015***	
	(-3.97)		(-3.71)	
T.Burden x Star		-0.151***		-0.152***
		(-17.85)		(-18.37)
T.Burden x Non-Star		0.014***		0.012***
		(3.47)		(2.58)
1(Star)		0.514***		0.420***
		(19.64)		(16.41)
Ln(Experience)	0.185***	0.175***	0.115***	0.106***
	(23.09)	(23.60)	(9.79)	(9.52)
Ln(Yr. Since Prev. Pat.)	-0.029	-0.029	0.004	0.001
	(-1.50)	(-1.52)	(0.21)	(0.07)
1(Indiv. Assignee)	-0.052	-0.057	-0.043	-0.048
	(-0.71)	(-0.80)	(-0.75)	(-0.84)
Inventor FE	Yes	Yes	Yes	Yes
Employer-by-City-by-Year FE	Yes	Yes	Yes	Yes
Number of Observations	12,564,053	12,564,053	10,148,672	10,148,672
Star=Non-Star (p-value)		0.000		0.000
$\bar{y}$	0.298		0.266	
Star $\bar{y}$		1.634		1.518
Non-Star $\bar{y}$		0.221		0.192

Table A7: **Non-Residence-based Specifications**

The dependent variables are inventor productivity, an inventor's scaled citations for patents filed in a productive year, and an indicator for whether an inventor changes job. The variable of interest is Time Burden and its interactions. Control variables are inventor experience (logged), inventor productivity over the previous 5 years (logged), the number of years since last patent was filed (logged), and an indicator for whether the inventor had an individual assignee designation in that year. Fixed effects for each specification are indicated in the footer. Standard errors are clustered at the inventor and assignee-level. All independent variables are lagged. All continuous independent variables are standardized.

Panel A: Inventor Productivity

	Patent Count					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.017***		-0.031***			
	(-3.73)		(-6.10)			
T.Burden x Star		-0.160***		-0.218***	-0.167***	-0.155***
		(-23.05)		(-20.62)	(-23.95)	(-21.55)
T.Burden x Non-Star		0.014***		0.016***	0.004	0.002
		(3.61)		(3.61)	(0.95)	(0.49)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-Year FE	Yes	Yes	No	No	Yes	No
Tech Class-by-Year FE	No	No	Yes	Yes	Yes	No
Employer-by-Tech Class-by-Year FE	No	No	No	No	No	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Star=Non-Star (p-value)		0.000		0.000	0.000	0.000
$\bar{y}$	0.815		0.815			
Star $\bar{y}$		4.376		4.376	4.376	4.376
Non-Star $\bar{y}$		0.619		0.619	0.619	0.619

Panel B: Scaled Citations

	Scaled Citations					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	-0.011		-0.008			
	(-1.26)		(-0.90)			
T.Burden x Star		-0.019		-0.008	-0.022*	-0.024**
		(-1.51)		(-0.57)	(-1.93)	(-1.97)
T.Burden x Non-Star		-0.009		-0.009	-0.014	-0.018**
		(-1.05)		(-0.91)	(-1.61)	(-2.05)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-Year FE	Yes	Yes	No	No	Yes	No
Tech Class-by-Year FE	No	No	Yes	Yes	Yes	No
Employer-by-Tech Class-by-Year FE	No	No	No	No	No	Yes
Number of Observations	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496	5,112,496
Star=Non-Star (p-value)		0.293		0.930	0.330	0.545
$\bar{y}$	1.333		1.333			
Star $\bar{y}$		4.103		4.103	4.103	4.103
Non-Star $\bar{y}$		1.001		1.001	1.001	1.001

Panel C: Inventor Mobility

	1(Change Jobs)					
	(1)	(2)	(3)	(4)	(5)	(6)
Time Burden	0.002***		0.001**			
	(5.61)		(2.49)			
T.Burden x Star		0.001		0.007***	0.001	0.001
		(1.32)		(4.64)	(0.95)	(0.79)
T.Burden x Non-Star		0.002***		0.001	0.002***	0.002***
		(5.55)		(1.63)	(3.92)	(3.65)
Controls / 1(Star)	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer-by-Year FE	Yes	Yes	No	No	Yes	No
Tech Class-by-Year FE	No	No	Yes	Yes	Yes	No
Employer-by-Tech Class-by-Year FE	No	No	No	No	No	Yes
Number of Observations	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053	12,564,053
Adj. R-sq	0.20	0.20	0.08	0.08	0.20	0.23
Star=Non-Star (p-value)		0.604		0.000	0.619	0.499
$\bar{y}$	0.100		0.100			
Star $\bar{y}$		0.169		0.169	0.169	0.169
Non-Star $\bar{y}$		0.096		0.096	0.096	0.096