Innovation through Inventor Mobility: Evidence from Non-Compete Agreements*

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Abstract

Proponents of restrictions on labor mobility argue that they provide innovation incentives to firms that outweigh negative worker outcomes like suppressed wages. Yet the causal effect of such policies on innovation is an open empirical question. Leveraging plausibly exogenous state-level changes in the enforceability of non-compete agreements, we find a significant negative effect on innovation: a 14% decrease in patenting for an average-sized increase in enforceability. This effect is even larger for the most novel and innovative patents and firms and is not simply attributable to competing explanations like patent-trade secret substitution or cross-state spillovers. Further analysis shows that these negative effects on innovation (i) cannot be explained by entry alone; and (ii) instead likely operate through reduced knowledge flows between firms when inventor moves decline and firms become more technologically isolated. Our findings suggest that labor mobility plays a crucial role in spreading knowledge across firms, with implications for a broad range of policies affecting worker movement.

Keywords: Innovation, Labor Mobility, Knowledge Diffusion, Non-Compete Agreements

JEL Codes: O31, O33, J08, J21, E24, K31

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1 Introduction

Policymakers are actively grappling with the optimality of a variety of policies that restrict labor mobility.[1] Proponents argue that such restrictions provide innovation incentives to firms that outweigh negative worker outcomes. Accordingly, these policies shape labor markets around the world. For example, a large share of the United States workforce is subject to non-compete agreements (NCAs)[2] – restrictive covenants in employment contracts that prevent employees from joining or starting a rival firm for some duration post-separation. The use of NCAs has grown in the US over the last few decades, in parallel with an increase in the legal enforceability of NCAs in many states.[3] More recently, however, some states have started to restrict the enforceability of NCAs, and NCAs have become a hotly contested public policy issue. In particular, the Federal Trade Commission (FTC) recently voted 3-2 to approve a rule to ban NCAs at the federal level.[4]

In this paper, we focus on an oft-touted benefit of NCAs: their potentially positive effect on innovation. As shown in **Figure 1**, recent data from the Bureau of Labor Statistics (BLS) National Longitudinal Survey of Youth (NLSY97)[5] suggest that NCAs are especially prevalent among professional sector "knowledge workers" – the executives, managers, computer specialists, engineers, researchers, and scientists, whom we might expect to be the most involved in innovation – with nearly 50% of these workers reporting being subject to an NCA.[6] Kitch (1980) summarizes the intuition behind their presumed positive effect on innovation: if "the courts leave employees free to leave the firm and exploit the information in competition with

[1] E.g., restrictions on immigration (Clemens et al., 2018); no-poach agreements (Polden, 2020); strong non-disclosure agreements (Hrdy and Seaman, 2024); occupational licensing (Pashigian, 1979); and others.

[2] For example, a 2017 survey of firms (Colvin and Shierholz, 2019) suggests that 30-45% of the full US private sector workforce is subject to an NCA.

[3] For example, between 2002 and 2013, there was a near-doubling in the number of legal cases decided where an employer sued a former employee to enforce an NCA – from 390 to 760 lawsuits (Simon and Loten, 2013). For additional details on the trend in enforceability, see **Appendix Figure 1**.

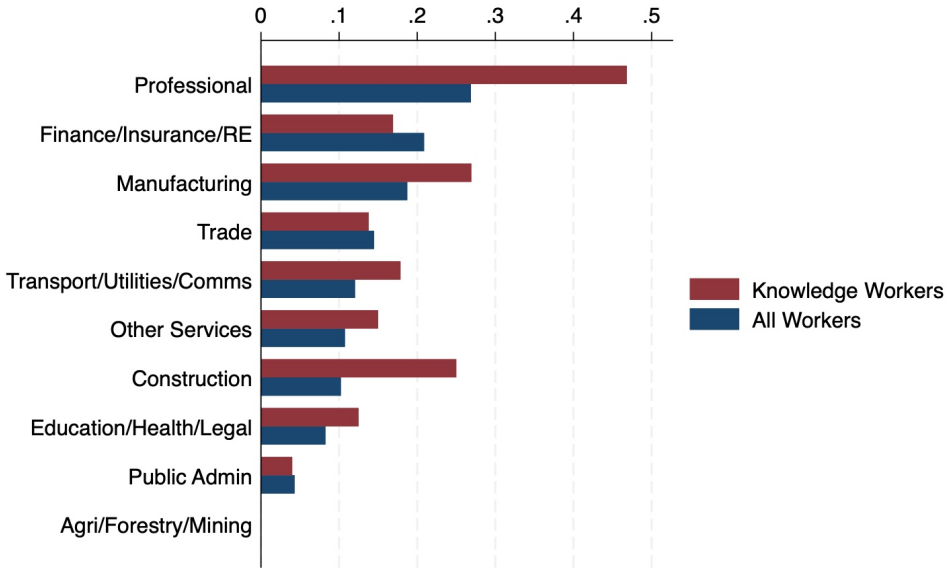
[4] In its final rule, the FTC cited the working version of this paper along with other contemporaneous working papers on innovation – He (2023) and Johnson et al. (2023a) – as well as others on related topics.

[5] For more information on the survey methodology, see Rothstein and Starr (2022).

[6] This statistic is particularly striking because it is likely underestimated. A 2014 survey of private sector workers indicates that employees have very little scope to negotiate these clauses, with many of them reporting they were not even *informed* about the clause until after their employment commenced (Starr et al., 2021).

the firm[,] this competition eliminates the return that would otherwise generate the incentive for investment in the production of that information." There is a common presumption in the legal literature and related policy discussions that it is this benefit to innovation that must be traded off against negative impacts on workers – e.g., reduced wages and mobility.

Figure 1: NCA Prevalence Across Industries and Worker Type



Share of workers from the NLSY 1997 cohort subject to NCAs by industry and worker type from 2017-2019. Knowledge workers refer to workers who serve in roles such as executives, managers, computer specialists, engineers, architects, scientists and researchers (CPS occupation codes 0010-2000). Data source: NLSY97.

However, there are reasons to think that NCAs might *harm* innovation. For example, NCAs could have a negative effect on entry when new firms cannot hire the workers they need because those workers are covered by incumbent NCAs. NCAs may also reduce the cross-firm flow of new ideas and technologies that facilitate knowledge diffusion and innovation spillovers. Indeed, some have argued that Silicon Valley's success relative to Route 128 stemmed in part from California's general refusal to enforce NCAs, enabling greater labor mobility and knowledge flows between firms (Gilson, 1999).

Thus, the net impact of NCAs on innovation remains theoretically ambiguous – while knowledge spillovers could enhance innovation, reduced protection of intellectual property could also

dampen firms' incentives to invest in R&D and innovation. This tradeoff ultimately requires comprehensive empirical analysis. In this paper, we therefore tackle the following two questions. First, what is the net impact of a change in NCA enforceability on innovation? And second, what channels explain this effect?

To estimate the effect of NCAs on innovation, we leverage judicial rulings and legislative policy changes as sources of plausibly exogenous variation in the state-level enforceability of NCAs.[7] And we measure innovation and inventor mobility using detailed US Patent and Trademark Office (USPTO) data on patent filings. Our analysis begins with a case study to investigate the effects of a single judicial change in Ohio that strengthened NCA enforceability. We find that patenting in Ohio fell significantly relative to a synthetic control, and that this decline was paralleled by a decrease in within-state inventor moves. We then estimate the effect of state-level changes in NCA enforceability on innovation using all variation nationwide from 1991 to 2016 and a state-year difference-in-differences approach. This more comprehensive analysis identifies an economically and statistically significant decline in patenting due to increases in NCA enforceability: for an increase in enforceability of the mean size in our sample, in-state patenting decreases by 14%. Thus, contrary to the hypothesis laid out by NCA proponents in policy debates, the net effect of NCAs on innovation seems to be negative.

This negative effect is particularly pronounced when focusing on more novel patents, patents in younger technological fields, and those by venture capital-funded firms, with effects roughly double the baseline estimates in each case. These striking differences across multiple measures of innovation quality suggest that our baseline results may actually understate NCAs' true impact on innovation. Rather than simply screening out low-value patents, highly enforceable NCAs appear to meaningfully hamper technological progress, with especially severe effects on breakthrough innovations.

Alternative explanations for this estimated decline in state-level patenting are also unlikely to explain our baseline results. Our results are not driven by changes in the propensity of

[7]This approach is in line with Garmaise (2009), Marx et al. (2009), Chen et al. (2018), Hausman and Lavetti (2021), Johnson et al. (2023b), and others.

firms to patent a given innovation (i.e., to substitute between patents and trade secrets), and cross-state spillovers are minimal in this setting such that they neither threaten the validity of our estimated treatment effect nor limit us from using our results to think about the effect of a national policy. We also provide a number of checks in the appendix to show that our results are robust to alternative sample definitions, econometric specifications, location definitions, etc.

To understand the mechanisms behind the overall effect of NCAs on innovation, we consider three specific channels through which NCAs may affect innovation: incumbent innovation incentives, firm entry, and labor mobility. The estimated negative net effect of highly enforceable NCAs on patenting indicates that incumbent innovation incentives are outweighed by one or both of the other channels. Therefore, we assess the entry and labor mobility channels individually to disentangle the overall net effect. We find that the entry channel (defined either in terms of new business applications or entrant patent applications) does not drive the overall decline in patenting. In contrast, we find compelling evidence that reduced labor mobility plays a central role: we observe both a statistically significant decline in inventor moves across firms and a substantial increase in the share of firms' citations to their own patents, suggesting decreased knowledge flows across organizations. These results suggest that labor mobility and knowledge diffusion may be key determinants of innovation effects in this setting.

This paper contributes to a growing literature on NCAs. A number of papers address specific NCA-related labor market outcomes. For example, Lipsitz and Starr (2022) and Young (2024) look at the effect of banning NCAs on wages for low-wage workers in Oregon and Austria, respectively. Balasubramanian et al. (2020) examine the impact of NCA restrictions in Hawaii on the careers of technology workers. And Johnson et al. (2023b) look at the implications of changes in enforceability for earnings and job mobility.

Several papers that consider the impact of NCAs on specific dimensions of innovation are also informative to our analysis here but, together, point to persistent empirical tensions in the literature. For example, Xiao (2022) finds that increased NCA enforceability leads to a *higher* rate of total innovation in the medical device industry. But Jeffers (2023) finds that increased NCA enforceability leads firms to increase investment in physical *but not* intangible capital like

R&D. Moreover, despite Xiao (2022)'s estimated overall increase in innovation, he estimates a decrease in "exploratory" medical device innovation under higher NCA enforceability, which seems at odds with Conti (2014)'s finding that higher NCA enforceability is associated with "riskier" R&D. And, while Barnett and Sichelman (2020) argue that "empirical studies fail to support a causal relationship between [NCAs], reduced labor mobility, and reduced innovation," Marx et al. (2009) show that an inadvertent repeal of Michigan's NCA policy (previously prohibiting NCAs) led to a decline in inventor mobility.

A number of papers also focus on the entry dimension, with different settings producing a mix of findings. Carlino (2021) finds no impact of increased NCA enforceability on entry in Michigan. In contrast, Johnson et al. (2023a) and Jeffers (2023) find that stronger NCA enforceability reduces entry based on the Census Bureau's Business Dynamics Statistics and matched employee-employer data from LinkedIn, respectively. Relatedly, Starr et al. (2018) and Baslandze (2022) find that higher NCA enforceability reduces spinouts. And Samila and Sorenson (2011) finds that stronger NCAs dampen the effects of venture capital (e.g., firm starts). Our paper contributes to this debate by bringing in evidence from the Census Bureau's Business Formation Statistics, which cover the universe of prospective new firms, and from Ewens and Marx (2024)'s Founding Patents dataset on young firm innovation. In this context, we find no impact of NCA enforceability on new firm entry and negative but statistically insignificant effects on newly founded firms' patenting.

Some of these contrasting results may be driven by different empirical settings or different focal policy changes. But, in tandem with the theoretical tensions discussed above, there remains a clear need for comprehensive evidence on how NCAs affect innovation across the broader economy. Our analysis fills this gap by exploiting a rich set of policy changes to provide robust causal evidence on the economy-wide impacts of NCAs on innovation. Relatively few papers consider the overall net impact of NCAs on innovation. The closest work to our findings on innovation are concurrent and complementary papers by He (2023) and Johnson et al. (2023a), which affirm our baseline patenting results. He (2023) finds that stronger NCA enforceability leads to a 33% decline in firm patent values over assets, while Johnson et al.

(2023a) find that an average-sized increase in NCA enforceability leads to 16-19% fewer citation-weighted patents over the following 10 years.[8] In addition to establishing the negative causal effect of NCAs on innovation, our paper provides novel evidence on the mechanisms driving this effect, highlighting how reduced inventor mobility dampens innovation by limiting knowledge spillovers across firms. In this regard, we also contribute to the broader literature on innovation incentives and spillovers.

This paper proceeds as follows. In Section 2, we describe the data used in this paper, including how we quantify changes in NCA enforceability. In Section 3, we introduce a case study to fix ideas before outlining our empirical approach for the all-state analysis. In Section 4, we present our all-state results that document the negative local average treatment effect of an increase in NCA enforceability on patenting, and explore to what extent these results reflect a true decline in innovation. In Section 5, we discuss our conceptual framework for the mechanisms through which NCA enforceability might affect innovation and examine the empirical evidence on the possible drivers of the observed overall effect. Finally, in Section 6, we discuss our results and briefly consider national policy counterfactuals.

2 Key Data

2.1 Index of State-Level Changes

In order to estimate the impact of NCAs on innovation, we track and quantify state-level changes in NCA enforceability by following Bishara (2011) and utilizing an index of state-level enforceability. Bishara (2011) develops a set of seven questions about enforceability, each of which is scored out of ten and then weighted by importance to create an index of state-level NCA enforceability over time out of a total possible score of 600.[9] A score of 600 means that

[8]Note that both unweighted and citation-weighted patents provide useful information about innovation dynamics. Our baseline results focus on unweighted patents, rather than citation-weighted patents, because changes in NCA enforceability may also affect citation networks and therefore the weighting scheme. However, we provide citation-weighted results in Section 4.2. The consistency of findings based on different econometric approaches, sample selection, time horizons, and outcome measures is striking, as discussed in the FTC's recent final rule.

[9]As an additional reference, the full text of these questions is detailed in Appendix B.

NCAs are very enforceable, and a score of 0 means that NCAs are hardly enforceable at all.

Bishara (2011) calculates this index for 1991 and 2011, and Marx (2022) extends the index to cover the years between 1991 and 2014. This paper newly extends the annual index through 2022 using a catalog of NCA enforceability changes broken down by state (e.g., due to state supreme court rulings or statutory changes) and focusing on changes that affect all workers rather than a subset of occupations (e.g., low-wage workers).[10] We then normalize the index on a 0 to 1 scale and focus our results on the years 1991-2016, which ensures a reasonable horizon of post-treatment effects.

We observe large and small changes in enforceability in both directions.[11] However, the majority of our changes in this period are "strengthenings" in NCA enforceability – i.e., changes greater than zero – which reflect the general trend toward stronger NCA enforceability during this period. The average magnitude of change in this period is 0.09 points in our baseline sample (as defined below), which approximately corresponds to a 9 percentage point change in enforceability.

2.2 US Patent Filings

We use patent filings from the USPTO (2022) PatentsView project to measure innovation. Patents are not a perfect measure of innovation – e.g., there are innovations that firms do not patent, either because they are not eligible to be patented or because the firm would prefer to keep the technology as a trade secret. Nonetheless, like much of the innovation literature, we contend that patents are a useful proxy for broader innovation, and one for which we have detailed disambiguated data for the universe of filings in the US since 1976. Although NCAs may not be directly relevant to protecting ideas already under patent, they have a material effect on firms' abilities to protect "tacit knowledge" – e.g., the work-in-progress research, follow-on innovations, research methods, negative knowledge, unpatentable byproducts of research, etc.,

[10] This is consistent with the goal of this paper, as limits on NCA enforceability with respect to low-wage workers are less likely to affect professional knowledge workers involved in innovation.

[11] **Appendix Figure 2** shows the distribution of non-zero changes to enforceability that we observe in the normalized index during this period.

which are generated alongside patent disclosures.

For the analysis discussed below, we restrict our sample to granted patents, with an identified filing location within the US, and we take each granted patent's date of application to construct our panel of state-level patenting by year. We also focus on patents assigned to US corporations.[12] And we restrict our sample to 1991-2016, as lags due to patent examination mean that post-2016 data are likely to be incomplete.[13] In addition to information about patenting inventors, the USPTO provides information about assignees (which are typically inventors' affiliated companies), inventor and assignee locations, technology fields, and citations. For our baseline estimates, we take the location of the assignee as the location of the patent.[14] However, in Appendix Section D.1 we also replicate our analysis when using inventor location as the patent location and when restricting our sample to patents where the assignee and inventor locations are the same; we find that our results are robust to both alternative specifications.

We use unweighted patent counts as our baseline measure of innovative activity to avoid conflating the effect of NCA enforceability on innovation with the effect of NCA enforceability on citation networks/flows. Nonetheless, in Section 4.2 we also use different citation measures to weight patents by approximations of their value rather than assuming (as we would when focusing on patent counts alone) that all patents are equally valuable or innovative. Our results are robust to this type of value-weighting.[15]

Finally, we use these data to construct a panel for the entire sample period on inventors and assignees linked to each other and to their patents across years. We see this data on inventor-specific mobility across US corporate assignees, which captures how often inventors switch from patenting with one firm to patenting with a different firm, as another unique contribution to

[12]We focus on corporate patenting – and exclude, e.g., government and academic patenting – to align with our interest in how NCAs affect firm incentives and innovative productivity.

[13]Data after 2016 are likely to also be incomplete in terms of forward citations, which we use to explore heterogeneity in the estimated treatment effect across patent value in Section 4.2 below.

[14]It does not appear to be the case that assignee locations are simply each assignee's headquarters. Rather, a review of the disambiguated assignees suggests that assignees list patent-specific locations (e.g., the office where the work was done) as their location on patent applications. See **Appendix Figure 12** for an example of this.

[15]These additional results both support the conclusions drawn from our baseline specification and suggest that enforceable NCAs are *not* simply screening out low-value patents and instead have real negative effects on valuable innovations.

this literature.[16]

2.3 Business Formation Statistics

We also utilize data on firm entry from the US Census Bureau (2022) BFS that measure new business applications and formations. We observe the total count of applications submitted for Employer Identification Numbers by entrepreneurs and corporations for each state.[17] BFS data are reported quarterly from 2004 to the present. For the analysis discussed below, we aggregate applications to the annual level to match the index of state-level NCA enforceability.

3 Empirical Approach

3.1 Identification

There are several challenges to estimating the causal impact of NCAs on innovation. For example, the use of NCAs by firms is likely to be endogenous to their future innovation. That is, if a firm anticipates that they are likely to have valuable innovations in the future, they may be more incentivized to include NCAs in their employment contracts. Ignoring this endogeneity could bias estimates of the impact of NCAs on innovation and spuriously suggest a positive relationship. For this reason, even where direct information on NCA use is available (e.g., for the executives of publicly listed firms), this information does not identify the causal effect of NCAs on innovation.

To deal with this endogeneity, we instead focus on NCA *enforceability* rather than actual employment contract terms. Enforceability itself may be endogenous in the cross-section if a firm's location choice depends on its innovativeness. For example, highly innovative firms may choose to locate in states with high NCA enforceability, but that would not imply the high

[16]Note that the outside option to such a move would include staying at the initial firm as well as moving to a non-patenting firm or to a patenting firm but in a non-patenting role.

[17]The data exclude applications for tax liens, estates, trusts, or certain financial filings, applications with no state-county geocodes, applications with certain NAICS codes in sector 11 (agriculture, forestry, fishing and hunting) or 92 (public administration) that have low transition rates, and applications in certain industries (e.g. private households, civic and social organizations).

degree of NCA enforceability causes that innovation. This type of spurious positive correlation in cross-sectional patenting may have contributed to the popular narrative that NCAs support innovation.

Instead, we use plausibly exogenous state-level *changes* in NCA enforceability as our independent variable. These changes reflect judicial rulings that modify the case law of what is and is not legally enforceable. Some changes also result from state legislation, which directly alter a state's statutes on NCA enforceability, overriding past legislation as well as past case law. Even in cases where one might worry that legislatures may change NCA policy in response to state-level conditions, Johnson et al. (2023b) shows that these changes are not predicted by a range of state-level characteristics.

3.2 Case Study: *Lake Land v. Columber* Decision

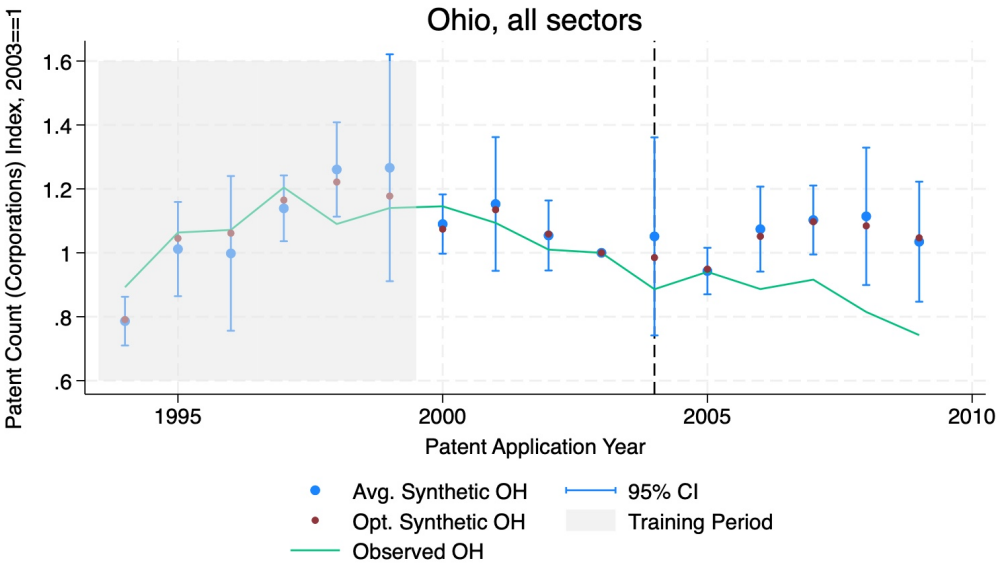
To fix ideas and provide intuition on the setting, we consider a case study before jumping into the analysis across all states. In March 2004, the Supreme Court of Ohio expanded the circumstances under which NCAs would be enforceable. Specifically, the Court's decision in *Lake Land Employment Group of Akron, LLC v. Columber* overturned the previous Ohio rule that an employee who signed an NCA after the commencement of employment had to be compensated for the agreement to be enforceable, ruling instead that continued employment would constitute adequate consideration to enforce an NCA going forward. This represented a sudden and substantial increase in the enforceability of Ohio NCAs.[18] This change in enforceability was both unanticipated and would have meant that Ohio firms could relatively costlessly distribute NCAs to their employees the next day without compensating them.

To assess how this change might have affected patenting, **Figure 2** compares Ohio patenting before and after the change to that of a synthetic control for Ohio constructed from states in our sample that never had a change in their NCA enforceability.[19] The green line in the figure documents observed Ohio patenting each year. The red dots represent the optimal synthetic

[18]This judicial ruling relates to the fifth Bishara index question, as detailed in Appendix Section B.
[19]The figure normalizes patenting to a state's patenting to its 2003 level for visibility.

control when we include all control states in the set of potential controls. The blue dots represent the average optimal synthetic control from 500 permutations where we randomly omit control states from the set of potential controls; from this, we can also construct standard errors and the 95% confidence intervals shown in the blue bars. This comparison suggests that Ohio patenting fell relative to the synthetic control after the *Lake Land* decision in 2004.

Figure 2: Ohio Patenting – Synthetic Control Comparison



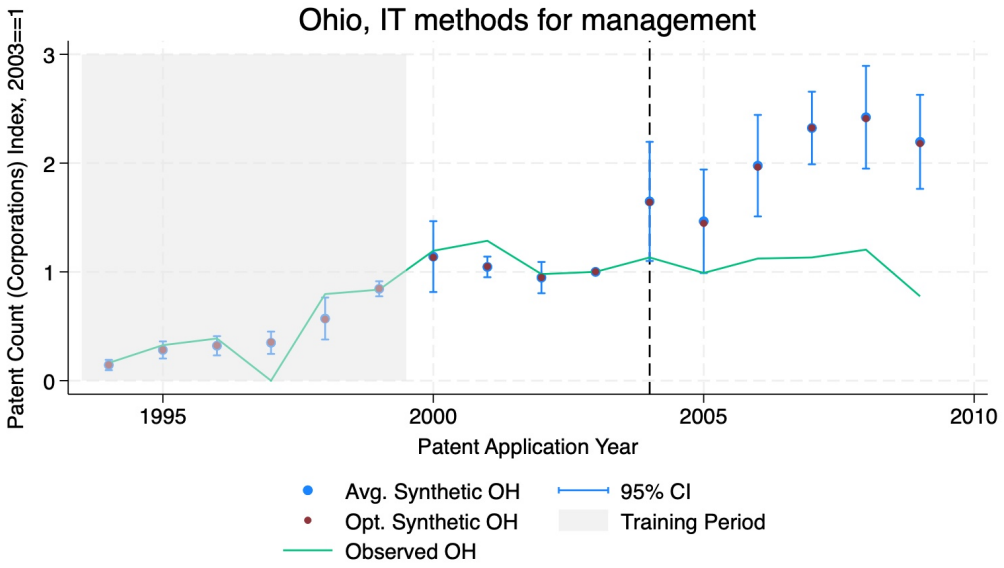
Comparison of observed Ohio patenting to synthetic Ohio patenting. The green line visualizes the trend in observed Ohio patenting. The red dots show the optimal synthetic control when all never-treated states are included as potential controls. The *synth* command in Stata constructs optimal weighted combination of untreated units in the training period as: 18% DC, 5% Mississippi, 5% West Virginia, 5% South Dakota, 5% Indiana, 4% New Jersey, 4% Tennessee, 4% New York, 4% Alabama, 4% Missouri, 3% Pennsylvania, 3% Colorado, 3% Virginia, 3% Oklahoma, 3% North Dakota, 3% Rhode Island, 3% Nebraska, 3% Utah, 3% Wyoming, 3% North Carolina, 3% New Hampshire, 3% Minnesota, 2% Montana, 2% New Mexico, 2% Washington, and 2% Nevada. The blue dots show the average synthetic control when we run 500 permutations of the analysis while randomly omitting various potential controls from the set under consideration. This approach also allows us to calculate the 95% confidence intervals show in the blue bars by bootstrapping the standard errors. All state-level patenting trends are indexed to 2003 levels. Data source: PatentsView. Details on the patent data are available in Section 2.2.

We can verify that this observed drop in Ohio patenting is not driven by industry compositional effects by also examining industry-level effects.[20] For example, by focusing on a high-tech industry, we can avoid confounds like Ohio's exposure to the transport industry dur-

[20]The World Intellectual Property Organization (WIPO) provides granular technology field information.

ing the Great Recession. **Figure 3** shows that there is also a sharp negative effect on Ohio patenting in the field of information technology (IT) methods for management following the *Lake Land* ruling.[21] It is intuitive that experience with and tacit knowledge around software would be valuable in a fast-moving and frontier field. And indeed, this comparison shows that Ohio patenting in IT methods fell to an even greater degree than aggregate patenting after the *Lake Land* decision in 2004.[22]

Figure 3: Ohio IT Methods Patenting – Synthetic Control Comparison



Comparison of observed Ohio patenting to synthetic Ohio patenting, now limited to the IT methods for management field defined by WIPO. The green line visualizes the trend in observed Ohio patenting. The red dots show the optimal synthetic control when all never-treated states are included as potential controls. The *synth* command in Stata constructs optimal weighted combination of untreated units in the training period as: 8% Indiana, 8% New Hampshire, 7% Minnesota, 7% Tennessee, 6% Missouri, 6% North Carolina, 6% New Jersey, 6% Pennsylvania, 6% New York, 6% District of Columbia, 5% Utah, 5% Virginia, 5% Washington, 5% Oklahoma, 5% Colorado, 5% Nevada, and 5% Nebraska. The blue dots show the average synthetic control when we run 500 permutations of the analysis while randomly omitting various potential controls from the set under consideration. This approach also allows us to calculate the 95% confidence intervals show in the blue bars by bootstrapping the standard errors. All state-level patenting trends are indexed to 2003 levels. Data source: PatentsView. Details on the patent data are available in Section 2.2.

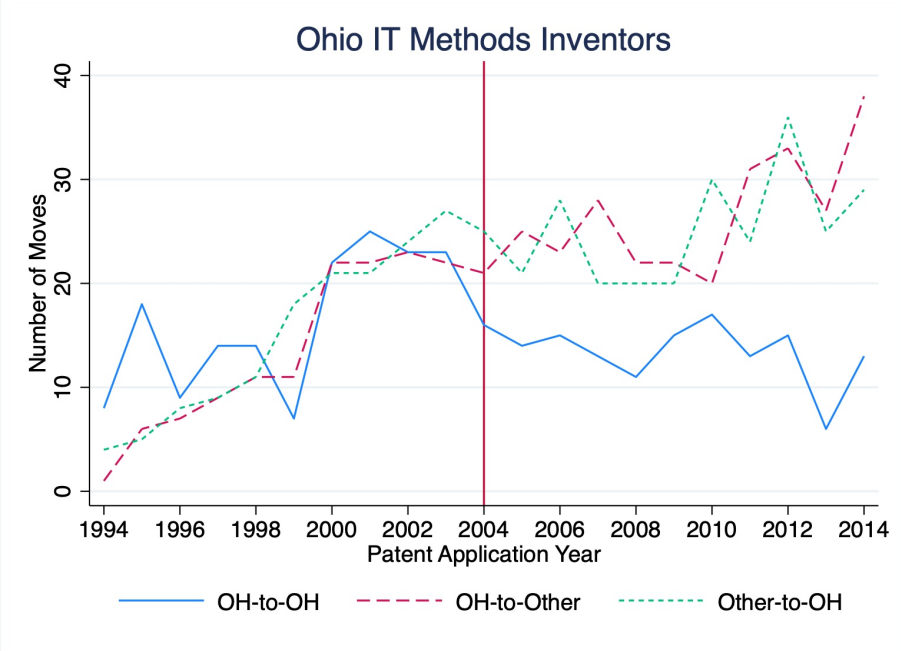
To confirm that it is the *Lake Land* decision driving these effects and not just some other

[21]The IT methods for management WIPO field relates to the IPC for "data processing methods, specifically adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes."

[22]These statistics also likely understate the amount of innovative activity going on, as only a subset of software is patentable.

event that happened around the same time, we can also look directly at in-state inventor mobility in Ohio during this period.[23] **Figure 4** shows the number of moves by IT methods inventors (i) within Ohio; (ii) out of Ohio; and (iii) into Ohio. Although the three series move together in the pre-period, the number of within-state moves drops sharply below the number of across-state moves in 2004 and afterward. This is precisely what one would expect an increase in NCA enforceability to achieve, as NCAs generally have within-state geographic scope. These coincident drops in within-state inventor mobility and patenting suggest that *Lake Land* played a significant role in changing the innovative landscape of Ohio by restricting worker mobility.

Figure 4: Moves by Ohio IT Methods Inventors – by Origin and Destination



Comparison of the number of moves each year by Ohio IT methods for management inventors who either moved within, out of, or into Ohio. A move is counted in this figure whenever we observe an inventor patenting historically at one firm and then switching to patenting at a new firm in year t. Data sources: PatentsView; clean organization lookup created by this paper. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 46.

[23] As described above, we define inventor mobility here as the number of times that we observe an inventor patenting historically at one firm and then switching to patenting at a new firm in year t. Inventor mobility thus captures *moves between patenting-related jobs at innovative firms*. Even a decline in moves driven by inventors who move to non-patenting jobs and thus out of our sample would be relevant to our analysis because such a response would still take the inventor out of the innovative ecosystem. Moreover, in our all-state analysis below, we consider the *share of inventors in the sample* who move and continue to see a proportional and statistically significant decline in inventor moves.

3.3 All-State Estimation

For the estimation across all states in our sample, we adopt a staggered difference-in-differences estimation approach: local projections difference-in-differences (LP-DiD) developed by Dube et al. (2023). This estimator is similar to other popular estimators like Callaway and Sant'Anna (2021) and Borusyak et al. (2021b) and shares their desirable features of, for example, avoiding the negative weights bias under staggered heterogeneous treatment effects of two-way fixed effects models. However, LP-DiD also permits non-absorbing and non-binary treatments as we have in our setting here.[24] Our estimating equation is the following:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} \qquad & \text{treatment (change in index)} \\ + \delta_{t+h} - \delta_{t-1} \qquad & \text{time effects} \\ + \epsilon_{i,t+h} \qquad & \text{for } h = -H, ..., H, \end{aligned} \tag{1}$$

where we restrict the sample to observations that are either (i) clean controls – i.e., not-yet or never treated states; or (ii) clean treatments – i.e., state-years with only one treatment in the past H years and with treatments greater than a threshold c.[25] In this specification, $y_{i,t+h} - y_{i,t-1}$ is the difference in the relevant outcome variable (log patents, log business applications, etc.). $\Delta X_{i,t}$ is the change in our continuous treatment variable – the normalized state-level index of NCA enforceability. LP-DiD allows for outcome lags to be included on the right-hand side of the estimating equation. Although not part of our baseline specification, we include a version of our estimation with these lags in Appendix Section D.2 to show robustness. Finally, we also control for time-fixed effects, δ. For our baseline specification we use: $H = 5$ years and $c = 15/600$.[26] We cluster standard errors at state-level and weight each state by its population

[24] Other more recent estimators have also been designed to permit such treatments – e.g., Gardner et al. (2024).

[25] For additional information on which states have strengthenings, weakenings, or neither in our baseline sample, see **Appendix Figure 3**.

[26] This low $c = 15/600$ threshold is conservative; **Table 1**'s third column shows that setting a higher threshold further strengthens our estimated effects, supporting the generalizability of our conclusions to other potential policy changes. **Table 1**'s second column also shows that our findings are robust to setting $c = 0/600$.

share in the previous year.[27]

The primary assumption necessary for the validity of the LP-DiD estimator is captured in the clean treatment and control conditions noted above, which require that a state must be either newly or not-yet treated such that it is not experiencing some ongoing treatment effect from a previous change in order to be included as either a treatment or control observation in the estimation. With these restrictions, we have 26 total treatments in 1991-2016 for our baseline sample, of which 17 are instances where NCA enforceability increased ("strengthenings"), and 9 are instances where enforceability decreased ("weakenings").[28]

4 All-State Results

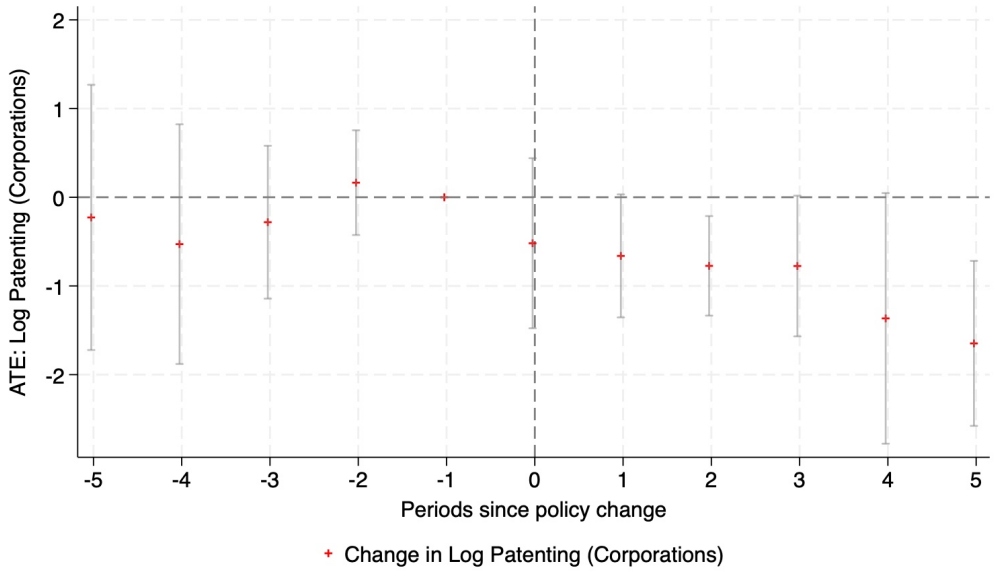
4.1 Baseline Results

Figure 5 and **Table 1**'s first column present our baseline estimates of the impact of all 26 changes in NCA enforceability in our baseline sample. These coefficients imply an economically and statistically significant decline in patenting due to increases in NCA enforceability. Using our baseline threshold of $c = 15$, they suggest that strengthening NCA enforceability from the median level observed in our sample to the maximum level observed in our sample (i.e., a move on the normalized index from 0.59 to 0.80) would decrease patenting by about 28% after 5 years.[29] For a more modest change in enforceability (e.g., of the average size observed in our sample), our estimates suggest that an increase of 0.09 points on the normalized index would decrease patenting by about 14% after 5 years. **Table 1**'s third column also shows that specifying a higher minimum threshold $c = 50$ for clean treatments results in marginally larger treatment effect estimates and smaller standard errors. This could be due to the greater salience of these larger changes and suggests that the estimated negative effect at $c = 15$ is not simply over-extrapolation based on smaller, potentially noisier changes in NCA enforceability.

[27] In Appendix Section D.3, we also present our results unweighted and weighted by their patent share in the previous year to show that our findings are robust to either alternative weighting scheme.

[28] We also include a number of other checks in Appendix Sections D.4 and D.5 to show that our results are

Figure 5: Estimated Effect of Changes in NCA Enforceability on Log Patent Count



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). See Table 1 notes.

robust to different permutations of this analysis.

[29]Note: predicted change is equal to $\exp(\beta_5 * \Delta X) - 1$.

Table 1: Effect of NCA Enforceability on Log Patenting

	Treatment: Δ NCA Index			
	1	2	3	4
Years Relative to Treatment	Baseline (c=15)	Lower Threshold (c=0)	Higher Threshold (c=50)	Accounting for Spillovers
-5	-0.227	-0.287	-0.098	-0.246
	(0.763)	(0.776)	(0.801)	(0.753)
-4	-0.529	-0.590	-0.356	-0.533
	(0.690)	(0.693)	(0.741)	(0.690)
-3	-0.281	-0.316	-0.090	-0.280
	(0.440)	(0.432)	(0.461)	(0.431)
-2	0.165	0.111	0.065	0.167
	(0.301)	(0.308)	(0.318)	(0.302)
-1	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.519	-0.488	-0.666	-0.581
	(0.489)	(0.483)	(0.473)	(0.499)
1	-0.661	-0.598	-0.635	-0.659
	(0.354)	(0.356)	(0.283)	(0.357)
2	-0.773	-0.658	-0.792	-0.776
	(0.286)	(0.288)	(0.261)	(0.285)
3	-0.775	-0.638	-0.999	-0.811
	(0.405)	(0.428)	(0.347)	(0.403)
4	-1.366	-1.222	-1.543	-1.363
	(0.721)	(0.739)	(0.749)	(0.722)
5	-1.648	-1.454	-1.769	-1.592
	(0.475)	(0.417)	(0.444)	(0.434)
Year FE	✓	✓	✓	✓
Constant	✓	✓	✓	✓
Observations	710	710	710	710
Δ After 5 Years for Average Treatment	-13.9 %	-9.2 %	-19.8 %	-13.4 %

Notes: Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting. Standard errors, clustered at the state level, in parentheses. Row titles indicate horizon h, relative to treatment ($h = 0$). Details on the econometric specification can be found in Equation 1 for specifications 1-3 and Equation 4. States are weighted by share of population in the previous year. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

4.2 Treatment Effects By Patent Innovativeness

Next, we consider which patents are the most affected by changes in NCA enforceability. In theory, an estimated negative effect of increases in NCA enforceability on patent counts could arise even if NCAs simply screen low-value patents out of the system in a socially efficient manner.[30] To test this theory, we compare how the estimated treatment effect changes across patents of heterogeneous quality (or, more precisely, heterogeneous *value*). If it were the case that highly enforceable NCAs simply screen low-value patents, we would expect to see the estimated treatment effect shrink as patent value increases.

A popular method in the existing literature to approximate patent value is to weight patents by their number of citations. Neither forward nor backward citations perfectly captures *value*, but these objects are seen as measuring correlated patent characteristics like impact and novelty. Forward citations are a common proxy for impact; they measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. Backward citations are a slightly less common measure, but recent research suggests that they may actually capture technological value more effectively;[31] they measure how many *previous* patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention.[32]

Table 2's first and second columns show the results of the same analysis from above, but now using impact-weighted patent counts (based on forward citations) or novelty-weighted patent counts (based on inverse backward citations) rather than raw patent counts. Our impact-weighted results (in blue) closely resemble our baseline findings, suggesting that the overall effect from above is not simply driven by a screening out of low-impact patents. Our novelty-weighted results (in red) are even stronger: an increase in enforceability of the average size observed in our sample (0.09 points) would decrease novelty-weighted patenting by as much as 21% after 5 years. The larger decline in novelty-weighted patenting implies that *high*-novelty

[30] For a discussion of patent screening, see Schankerman and Schuett (2022) and others.

[31] E.g., see the discussion in Jaffe and de Rassenfosse (2017).

[32] For our novelty weighting, we weight patents by $1/(\text{backward cites} + 1)$. At the patent level, backward and forward citations are also winsorized to keep a single (either true or mismeasured) outlier patent from driving the results.

(and therefore likely *high*-value) patents are the inventions that are disproportionately affected by changes in NCA enforceability.

In addition to thinking about patent novelty using citations, we can think about the novelty of entire fields. **Table 2**'s third and fourth columns show the same analysis as above but now broken down by WIPO field age (i.e., when a field received its first patent application).[33] We classify a field as a 'young' field if the first patent assigned to this field was issued after 1970. These results again suggest that it is patents in younger fields that are disproportionately affected by changes in NCA enforceability. We find that an increase in enforceability of the average size observed in our sample (0.09 points) causes patenting in young fields to fall by as much as 32% after 5 years, compared to 13% for old fields. This is intuitive – e.g., as discussed above with respect to IT methods for management, experience with and tacit knowledge around software seems likely to be valuable in a fast-moving and frontier field – but also striking that we lose not just average patents but some of the *most innovative and most novel* patents when inventor mobility is restricted.

Another strategy to approximate the value of innovations captured in patents is to consider which patent assignees have ever received VC funding. The existing literature suggests that VC-funded firms tend to produce highly innovative patents.[34] **Table 2**'s fifth and sixth columns show the estimated treatment effect of changes in NCA enforceability on patenting separately for firms with VC funding and those without VC funding.[35] Although the estimated effects on both VC-funded firms' patents (in red) and non-VC-funded firms' patents (in blue) are negative and statistically significant at the 5 year mark, changes in NCA enforceability have a more pronounced effect on the patenting of VC-funded firms – an increase in enforceability of the average size (0.09 points) would be expected to decrease VC-funded firms' patenting by

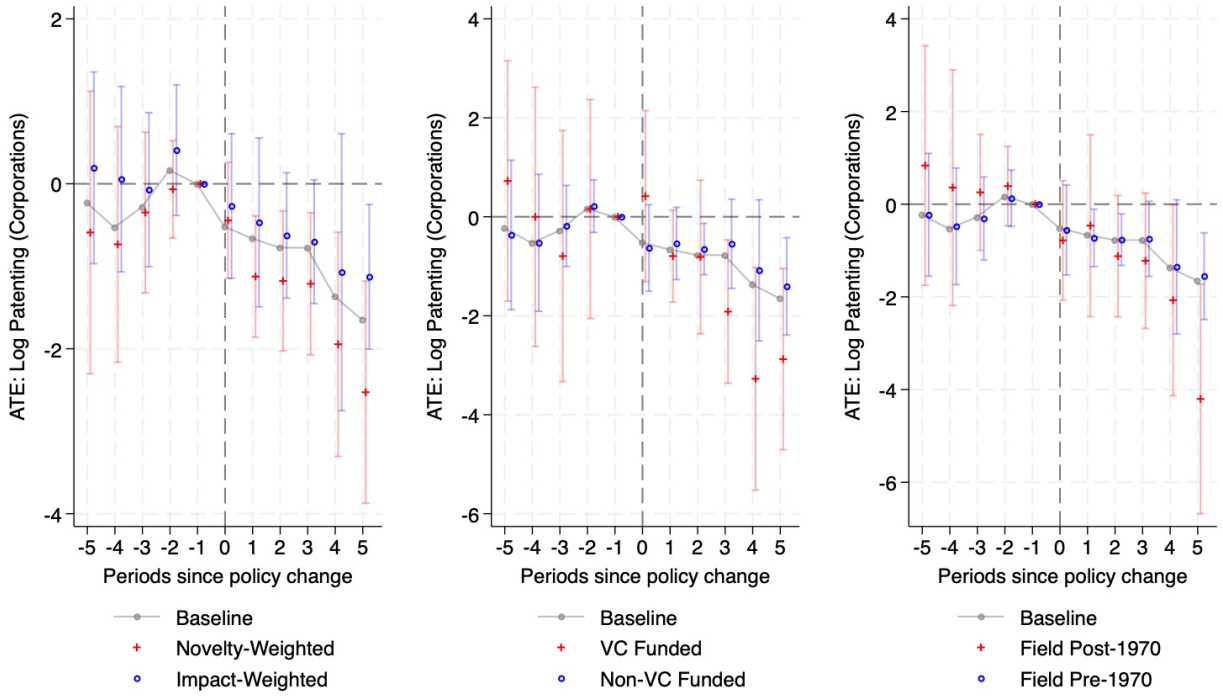
[33]For example, the IT methods for management field received its first patent application in 1972.

[34]Some existing evidence suggests that the "higher innovativeness of venture-funded firms is due to the selection process of the venture capitalist prior to the funding rather than to the venture funding itself" (Engel and Keilbach, 2007). However, there could be a mixed effect here given Samila and Sorenson (2011)'s findings that venture capital is more effective with respect to patenting, firm starts, and employment under weak NCA enforceability.

[35]To identify patent-level VC-funding, we use a dataset from Ewens and Marx (2024) that provides patent assignees matched to Pitchbook data and indicates whether an assignee ever received VC funding.

23% after 5 years. This finding again suggests that high-value patents are particularly sensitive to changes in NCA policies and contradicts the screening out hypothesis.

Figure 6: LP-DiD Coefficient Estimates: By Innovativeness



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on (a) the log of state-level corporate patenting weighted by forward citations in year h relative to the time of the policy change ($h = 0$), and weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$), (b) the log of state-level corporate patenting by firms who received venture capital funding versus those that did not, (c) the log of state-level corporate patenting by the age of the WIPO field. See Table 2 notes.

The overall effect of NCA enforceability by patent innovativeness is summarized in **Figure 6**. Taken together, these results suggest that the baseline findings from Section 4.1 may actually understate the degree to which innovation is affected by changes in NCA policies. The stronger effects observed for novelty-weighted and VC-funded patenting indicate that it may be the *most* innovative patents that are especially affected by changes in NCA enforceability, rather than the low-value inventions.

Table 2: Effect of NCA Enforceability on Log Patenting by Innovativeness

	Treatment: Δ NCA Index					
	1	2	3	4	5	6
Years Relative to Treatment	Impact Weighted	Novelty Weighted	Young Field	Old Field	VC Funded	Non-VC Funded
-5	0.194	-0.590	0.835	-0.228	0.724	-0.366
	(0.593)	(0.874)	(1.319)	(0.676)	(1.239)	(0.770)
-4	0.056	-0.734	0.358	-0.477	-0.000	-0.525
	(0.573)	(0.729)	(1.298)	(0.642)	(1.336)	(0.706)
-3	-0.071	-0.348	0.255	-0.308	-0.793	-0.185
	(0.476)	(0.497)	(0.639)	(0.457)	(1.295)	(0.418)
-2	0.409	-0.067	0.390	0.128	0.157	0.216
	(0.404)	(0.301)	(0.437)	(0.310)	(1.129)	(0.271)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.269	-0.445	-0.781	-0.557	0.418	-0.629
	(0.447)	(0.359)	(0.658)	(0.496)	(0.882)	(0.446)
1	-0.468	-1.124	-0.463	-0.728	-0.794	-0.538
	(0.522)	(0.376)	(1.001)	(0.317)	(0.475)	(0.373)
2	-0.626	-1.178	-1.121	-0.765	-0.810	-0.653
	(0.388)	(0.433)	(0.667)	(0.284)	(0.792)	(0.265)
3	-0.702	-1.212	-1.221	-0.748	-1.915	-0.544
	(0.382)	(0.440)	(0.746)	(0.413)	(0.738)	(0.460)
4	-1.071	-1.945	-2.073	-1.352	-3.273	-1.081
	(0.857)	(0.694)	(1.051)	(0.738)	(1.148)	(0.728)
5	-1.127	-2.526	-4.202	-1.552	-2.875	-1.405
	(0.447)	(0.687)	(1.264)	(0.477)	(0.935)	(0.502)
Year FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
Observations	710	710	710	710	710	710
Δ After 5 Years for Average Treatment	-9.7 %	-20.5 %	-31.7 %	-13.1 %	-23.0 %	-12.0 %

Notes: See Table 1 notes. Forward citations measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. Backward citations measure how many previous patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. Inverse backward citations are defined to be equal to $1/(\text{backward cites} + 1)$. Forward and backward citations are windsorized at the 1st and 99th percentiles. 'Young fields' are those with their first patent after 1970. For patents with multiple WIPO fields, we assign them to the first listed field for the purposes of the estimation. Data sources: as in Table 1; and data on patent assignee VC funding compiled by Ewens and Marx (2024).

4.3 Alternative Explanations

Before concluding that our headline estimates represent a true *innovation* effect, we must also consider potential alternative explanations. In this section, we evaluate the extent to which the estimated negative effect might instead reflect (i) firms substituting away from patents to trade secrets (i.e., decreasing their propensity to patent a given innovation), or (ii) cross-state spillovers moving innovation activity out of the treated state. Neither of these alternative explanations explain our results. As discussed above, the appendix also provides a number of other checks to show that our results are robust to alternative sample definitions, econometric specifications, etc. Therefore, our results do appear to be driven by changes in innovation as such.

4.3.1 Substitution Between Patents and Trade Secrets

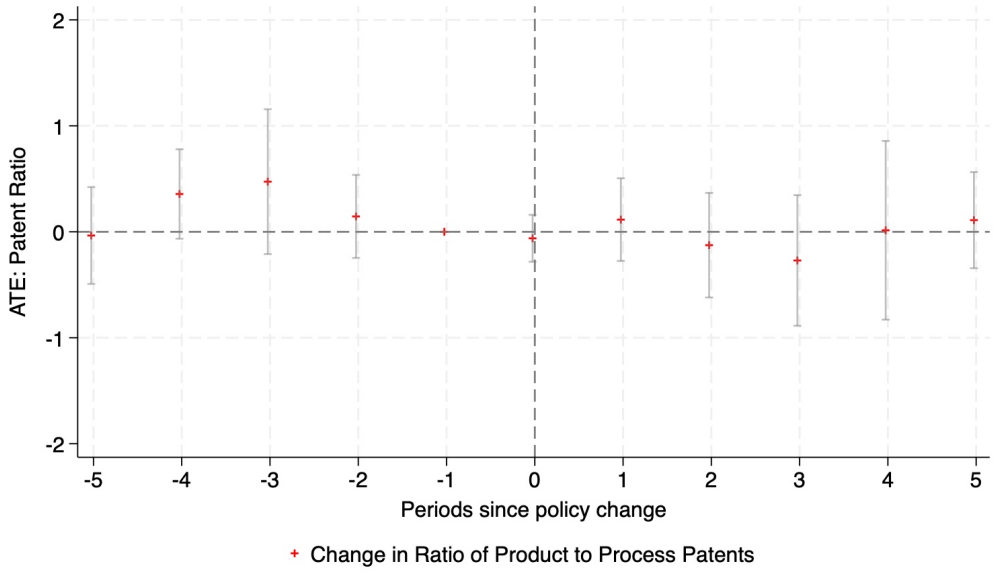
NCAs may affect not only innovation but also the propensity of firms to patent a given innovation. That is, if firms view NCAs and patents as substitutes in protecting their inventions and ideas, we might pick up substitution effects alongside innovation effects if firms increase their reliance on trade secrets under stronger NCA enforceability and forego patenting. Theoretically, such substitution is unlikely to be an issue here. Discussions with legal scholars have revealed that the risk of not patenting an eligible invention is generally too large for firms to adopt such a strategy, even under fully enforceable NCAs – e.g., if a competitor independently invents and patents your same invention, it obtains the right to exclude you from use of the invention. And, even short of a competitor *patenting* your invention, independent discovery and reverse engineering would destroy any right you have to exclude others.

Empirically, we can consider the treatment effect of changes in NCA enforceability on the relative frequencies of product and process patents.[36] Product innovations are hard to protect through trade secrets alone due to the potential for reverse-engineering, so firms are unlikely to choose not to patent eligible product innovations even in the face of high NCA enforceability.

[36]Patents are categorized as process or product patents based on an index by Heinrich et al. (2022). We focus on product-only and process-only patents, and we do not take a stance here on the appropriate classification of mixed patents that involve both products and processes.

But substitution between trade secrets and process patents may be more of a concern. Therefore, if firms use trade secrets as a substitute for patents under stronger NCA enforceability, we should see most (if not all) of our effect operating through the process-only patents channel such that the relative frequency of product- and process-only patents changes too. Our results in **Figure 7** show, however, that the mix of product and process patents granted within a state does not change in response to changes in NCA enforceability, such that substitution away from (process) patenting seems unlikely to be generating our results. This supports the interpretation of our baseline estimates as reflecting a true impact of NCAs on innovation rather than simply capturing ancillary substitution behavior.[37]

Figure 7: Estimated Effect of Changes in NCA Enforceability on the Ratio of Product-Only Patents to Process-Only Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the ratio of product-only patents to process-only patents in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; Heinrich et al. (2022) patent categorizations. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

[37]Consistent with our findings, Greenwood et al. (2024) finds that firms do not decrease their reliance on trade secrets when NCAs are made less enforceable. They suggest that trade secrets are more likely to be complements to NCAs than substitutes.

4.3.2 Cross-State Spillovers

So far, we have also estimated the *state-level* impact of changes in NCA enforceabiliity. However, in order to confirm the validity of SUTVA and to extrapolate to the expected effects of a national policy (e.g., the FTC's recent ban), we need to account for the potential impact of cross-state spillover effects. Accounting for certain spillover effects could intensify our estimated net effect. For example, accounting for how declines in patenting in Ohio would inhibit follow-on innovation in other states could increase our estimated magnitudes. However, accounting for other spillover effects could dampen our net effect. For example, if workers move states to escape NCAs (following an increase in enforceability in their initial state of residence), they may increase innovation in their destination state. To ensure that our estimated effect is conservative, therefore, we now also control for out-of-state migration effects, which have the potential to dampen our baseline estimated treatment effect.

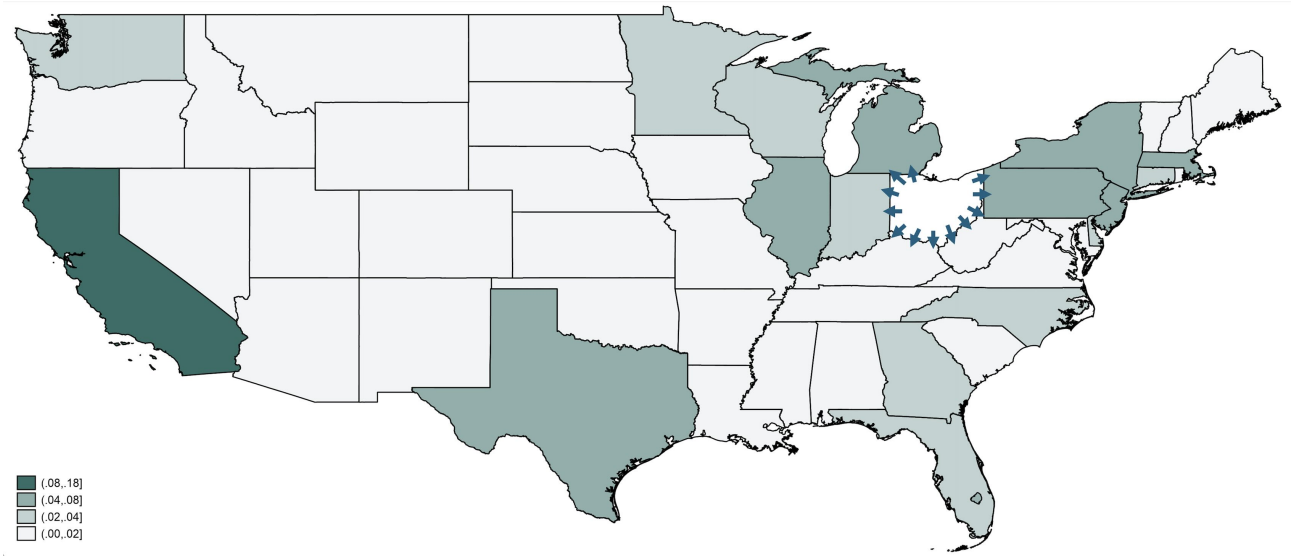
Inventor migration patterns have stable determinants (e.g., distance, industry mix, demographics, and relative economy size). For example, **Figure 8** shows the relative shares with which inventors moving out of Ohio end up in other states. California is the most common, as might be expected based on factors like the relative size of its inventive economy. However, states like Wisconsin, Illinois, Indiana, and Pennsylvania are also well-represented, as might be expected based on factors like distance of migration. **Appendix Figure 24** shows that these migration shares (conditional on out-of-state migration) are relatively constant over time.

Given this, we can define a gravity-style control for the cumulative exposure of state i to all other states' changes in enforceability.[38] Specifically, we can specify the following term to capture state i's exposure to movers out of other states due to other states' changes in enforceability as a percentage of i's initial inventor population:

$$\lambda_{i,t+h} := 100 \cdot \left(\sum_{\forall o \neq i} \underbrace{wm_{oi,t-1}}_{i\text{'s exp. to } o} \cdot \underbrace{\mathbb{I}_{o,t} \cdot m_{o,t-1} \cdot [M_{o,t+h} - M_{o,t-1}]}_{\text{change in \# movers out of } o} \right) / \underbrace{P_{i,t-1}}_{\text{\# inventors in } i}, \tag{2}$$

[38] This control is in the style of existing work such as Dubé et al. (2017); Borusyak and Hull (2023); Borusyak et al. (2021a); Peri et al. (2015); Kerr and Lincoln (2010); and Card (2001). However, it is somewhat novel in that it captures exposure to multiple events rather than a singular event.

Figure 8: Example Mover Destinations (Ohio)



Map of destination states for Ohio inventors who move out of the state. Darker colors indicate states that are more frequent recipients of Ohio inventors, as detailed in the legend. Inventor moves are defined as above. Data sources: PatentsView; clean organization lookup. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 46.

where $wm_{oi,t}$ is the share of inventors who move out of state o in year t that end up in state i; $m_{o,t}$ is the level count of inventors moving out of state o in year t; $M_{o,t}$ is the log count of inventors moving out of state o in year t; and $P_{i,t}$ is the level inventor population in state i in year t.

With this term in mind, we can predict the change in the number of inventors moving out of state that is induced by a change in NCA policy in the first stage of the following two-stage regression, and then use that predicted change to include a predicted $\hat{\lambda}$ as a covariate in the second stage version of our baseline specification:[39]

$$1. \quad M_{o,t+h} - M_{o,t-1} = \theta_h \cdot \mathbb{I}_{o,t} \cdot \Delta X_{o,t} + \gamma_{t+h} - \gamma_{t-1} + \varepsilon^1_{o,t+h} \tag{3}$$

$$2. \quad Y_{i,t+h} - Y_{i,t-1} = \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} + \delta_{t+h} - \delta_{t-1} + \rho_h \cdot \hat{\lambda}_{i,t+h} + \varepsilon^2_{i,t+h} \tag{4}$$

Here, ρ is a parameter to test for the presence of spillovers through inventor moves.

[39]The two identifying assumptions necessary for this approach are: (i) treatment in state i affects state j patenting only proportionally to historical migration flows; and (ii) treatment in state i is exogenous to things happening in state j.

This analysis suggests that there are no statistically significant cross-state spillover effects from migration. The estimated coefficient ρ of the impact on a destination state's patenting due to a change in a treated state's enforceability is close to 0 in all periods (**Appendix Figure 25**).[40] This result is consistent with existing literature that finds that accounting for individual workers' out-of-state migration does not change optimal state-level policies, such as income taxation (Mazerov, 2023). Accordingly, **Table 1**'s fourth column shows that the treatment effects estimated after correcting for cross-state spillovers are essentially identical to those from our baseline specification.[41]

5 Channels Analysis

Having ruled out a number of competing theories for how NCA enforceability could lead to a decline in patenting without true innovation effects, we now turn to assess what channels might explain our baseline results. **Figure 9** summarizes our conceptual framework. Specifically, we consider three channels through which NCAs may be expected to affect innovation. First, NCAs might increase innovation due to **incumbent innovation** incentives. Just as patents are thought to encourage innovation by allowing firms to better appropriate the returns on R&D expenditures (e.g., by allowing them to charge higher markups on innovative products for a period of time following a novel invention), NCAs may also incentivize incumbent innovation by helping firms protect their confidential information (e.g., trade secrets, tacit knowledge, negative knowledge, etc.) and maintain a competitive advantage over rivals.

However, incumbent firms are not the only source of innovation. Our second channel, **firm entry**, is important as well. Garcia-Macia et al. (2019) estimates, for example, that firm entry accounts for approximately 20% of TFP growth in the US. But, without empirical analysis, the effect of NCAs on entry is theoretically ambiguous. On the one hand, NCAs might

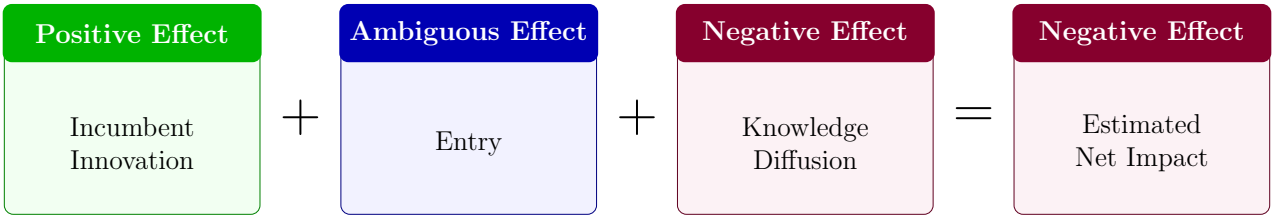
[40] Details on the first stage results of this regression analysis can be found in **Appendix Figure 26**. There, we see no statistically significant impact of change in NCA enforceability on out-of-state moves, with F-stat of the treatment indicators $\in [0, 3]$ for all $h \in [-5, 5]$.

[41] Note that this is consistent with but conservative relative to Johnson et al. (2023a)'s conclusion that economy-wide losses are *larger* than state-level losses.

have a positive effect on firm entry to the extent that they increase the expected profits of a successful entrant (i.e., as with incumbents, by allowing firms to earn super-normal profits on their innovations or by reducing the wages and bargaining power of workers). However, NCAs could also have a negative effect on entry by imposing barriers to entry. For example, a worker covered by an NCA is legally prohibited from entering the market as a rival firm. Moreover, even if a would-be entrepreneur is not covered by an NCA, they may still find it difficult to enter the market if most workers in the local industry are covered by NCAs such that it proves difficult to recruit talent. Among other things, this paper assesses the net impact of NCAs on this entry channel, which is otherwise uncertain.

Third, NCAs may negatively affect productivity and innovation by reducing **knowledge diffusion** – i.e., the flow of new ideas and technologies between firms. This channel impacts the ability of other firms to learn about and improve upon the new technologies produced by rivals.[42] If workers moving between firms is an important mechanism through which innovations diffuse, then direct limits on employee mobility will hamper this channel of knowledge flows.

Figure 9: Summary of Conceptual Framework



5.1 Entry

To start untangling the mechanism(s) behind our results, we estimate the effect of changes in NCA enforceability on new business applications using the Census BFS data discussed above. **Table 3**'s first column shows that there is no statistically significant effect of changes in NCA enforceability on entry in the BFS – and certainly not a decline of the magnitude we see for patenting overall. In Appendix D.7 we additionally show these results are robust to using four

[42]This channel has been pointed to as a potential explanation behind Silicon Valley's growth, for example, where NCAs are almost never enforceable.

or eight quarter business *formations* from the BFS as our measure of entry.

That said, this set of firms may be overly inclusive (i.e., include non-innovating firms). Therefore, we also estimate (i) a version of our baseline patenting results looking only at firms founded in the same year as or after a patent application was filed;[43] and (ii) a version of our baseline patenting results looking only at firms who have previously patented (i.e., where we would expect to see no effect if entrants were driving the overall effect shown above).[44] **Table 3**'s second and third columns show that (i) there is a negative but statistically insignificant effect of changes in NCA enforceability on patents assigned to newly founded firms (in red); and (ii) there is a larger negative and statistically significant effect of changes in NCA enforceability on patents assigned to incumbents (in blue) – similar to that of our baseline estimates.[45] Taken together, these results suggest that highly innovative entrants may be negatively affected by increases in NCA enforceability (unlike entrants overall). However, given the impact on incumbents-only patenting and the relative statistical significance of the results, the observed decline in overall patenting *cannot* be explained solely by reduced entry.

5.2 Labor Mobility and Knowledge Diffusion

Given that our findings cannot be fully explained by reduced firm entry, we now examine labor mobility and associated knowledge diffusion as potential key channels through which NCA enforceability affects innovation. Labor mobility could affect innovation through multiple mechanisms. First, when workers can move freely between firms, they carry with them not just their formal knowledge but also tacit knowledge, work practices, and expertise that can spark new innovations at their destination firms. Second, mobile workers create and maintain professional networks that facilitate knowledge exchange even after they have moved. Third, the

[43]Patent assignee founding years come from a dataset compiled by Ewens and Marx (2024). This analysis differs from the BFS analysis not only in its focus on innovative firms but also in that it essentially weights entry by patenting so that we can capture a single but highly innovative firm as important.

[44]That is, excluding entrants who are patenting for the first time. In Appendix D.7, we show that this incumbents-only result is also robust to defining incumbents as the set of patent assignees *not* linked to a newly founded firm.

[45]Although this may be somewhat mechanical given that a large share of patenting is done by incumbents, it still demonstrates that there are real effects of changes in NCA enforceability on incumbent patenting specifically.

promise of mobility may incentivize workers to maintain high effort and creative engagement, knowing their skills will be valued in the broader labor market.

As shown in **Table 3**'s fourth column, we find strong evidence when examining inventor mobility directly that increases in NCA enforceability significantly reduce worker movement between firms. We measure inventor moves from the patent data using disambiguated inventor and assignee names.[46] For an average-sized increase in enforceability (0.09 points), the share of inventors changing employers drops by 33% after five years. **Table 3**'s fifth column shows that this effect is even more pronounced among inventors at VC-funded firms, where mobility declines by 50% – consistent with our earlier finding that the most innovative segments of the economy are particularly sensitive to NCA policy. The larger effect for VC-funded firms is intuitive: these firms often operate at the technological frontier where tacit knowledge and novel approaches are especially valuable, making their inventors both more likely to be covered by NCAs and more constrained by them when seeking new opportunities.

This reduction in inventor mobility appears to directly impact the flow of knowledge between firms, as evidenced by changes in patent citation patterns. **Table 3**'s sixth column shows that that stronger NCA enforeability corresponds to an increase in self-citation by firms (or, equivalently, a decrease in the share of citations to work by other firms). Following an average-sized increase in NCA enforceability, firms' share of self-citations (i.e., citations to their own prior patents) increases by 17%. This growing technological isolation suggests that reduced labor mobility impairs knowledge spillovers across firms. When inventors are constrained from moving, firms appear to build more heavily on their own prior innovations rather than incorporating insights and approaches from across the broader innovative ecosystem. This pattern is particularly concerning given evidence from other contexts that breakthrough innovations often emerge from recombining ideas across domains and organizations.

The parallel timing and magnitudes of the declines in inventor mobility and increases in

[46]To ensure that we are accurately measuring inventors who move across firms, we also contribute a novel clean organization lookup that further disambiguates assignee names from the USPTO data. This is essential, as it would be incorrect to consider an inventor we see attached to multiple misspellings of one organization name as moving. An example mover is included for reference in **Appendix Figure 13**.

self-citation provide compelling evidence that labor mobility is a crucial channel through which NCA enforceability affects aggregate innovation. Rather than simply protecting legitimate firm interests, excessive NCA enforceability appears to create technological silos that reduce the fertility of the broader innovation ecosystem. This interpretation aligns with historical examples, such as the role that high labor mobility played in Silicon Valley's emergence as a technology hub, and suggests that policies restricting worker mobility may have significant unintended consequences for innovation. Given the importance of interpersonal interaction in idea diffusion, these findings suggest that labor mobility is an important channel of innovative knowledge diffusion (which is itself an input to aggregate innovation).[47]

[47]See, for example, Singh (2005), Agrawal et al. (2006), Agrawal et al. (2008), and others.

Table 3: Channels Analysis Results

	Channels Analysis					
	1	2	3	4	5	6
Years Relative to Treatment	Business Apps	New Firm Patenting	Incumbent Patenting	% Inventor Moves	% Inventor Moves (VC)	% Cites Own-Firm
-5	-0.265	-0.336	-0.355	-0.004	-0.011	-0.002
	(0.308)	(0.845)	(0.821)	(0.004)	(0.012)	(0.105)
-4	-0.039	-0.629	-0.594	-0.002	-0.008	0.068
	(0.259)	(0.763)	(0.747)	(0.004)	(0.013)	(0.095)
-3	-0.004	-0.358	-0.338	0.005	0.042	-0.042
	(0.112)	(0.450)	(0.443)	(0.006)	(0.042)	(0.066)
-2	0.034	-0.137	0.185	-0.005	-0.017	-0.029
	(0.057)	(0.391)	(0.316)	(0.004)	(0.026)	(0.063)
-1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0	-0.089	-0.000	-0.587	-0.006	-0.012	-0.046
	(0.073)	(0.443)	(0.512)	(0.005)	(0.016)	(0.077)
1	-0.090	0.339	-0.656	0.004	0.018	-0.033
	(0.152)	(0.438)	(0.392)	(0.008)	(0.037)	(0.081)
2	-0.059	-0.325	-0.751	-0.015	-0.018	0.086
	(0.222)	(0.731)	(0.313)	(0.004)	(0.011)	(0.121)
3	-0.029	-0.193	-0.778	-0.010	-0.042	0.153
	(0.333)	(0.519)	(0.438)	(0.006)	(0.019)	(0.106)
4	0.041	-0.960	-1.377	-0.017	-0.017	0.213
	(0.421)	(0.747)	(0.753)	(0.004)	(0.020)	(0.131)
5	0.309	-1.360	-1.640	-0.017	-0.031	0.279
	(0.442)	(0.788)	(0.502)	(0.005)	(0.014)	(0.100)
Year FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
Observations	710	710	710	710	710	710
Δ After 5 Years for Average Treatment	2.8 %	-11.6 %	-13.8 %	-0.1 p.p. (-32.9 %)	-0.3 p.p. (-50.0 %)	2.6 p.p. (17.0 %)

Notes: Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on (1) business applications, the log of state-level corporate patenting for (2) new firms and (3) incumbents, the % of inventors who move firms for (4) all firms and (5) VC funded firms, and (6) the % of citations to patents by the same firm. See Table 1 notes for more details. Data sources: as in Table 1; and data on patent assignee founding years compiled by Ewens and Marx (2024); data on patent assignee VC funding compiled by Ewens and Marx (2024). Details on the business applications data are available in Section 2.3.

6 Discussion

Using these results, we can also think about the effect of hypothetical federal policies that weaken NCA enforceability nationwide. Our preferred policy counterfactual is one that matches up well with the average treatments observed in our data.[48] Therefore, we consider what the effect of a 0.09 point weakening in our normalized index would do to patenting across the country.[49] Given the lack of significant spillovers in the other direction above, we use our baseline β estimate from 5 years after a hypothetical change for this exercise. Our point estimates suggest that this federal decrease in national enforceability would increase patenting by 14% nationwide.

One could take our results a step further and extrapolate linearly to think about what these results might imply for the FTC's recent ban on NCAs. We heavily caveat such extrapolation. However, the sign and economically significant magnitude of the predicted effect points to a large potential upside to innovation of such a ban. Our estimates presented above suggest that, 5 years after such a change, patenting would more than double nationwide.

The preceding analysis raises a number of other considerations that are beyond the scope of this paper due to data limitations, but which we hope to explore in future work. For example, our focus on patented inventions necessarily excludes a potentially significant portion of non-patented innovative activity. Moreover, this analysis examines the effects of NCA enforceability at the state and national levels, which likely masks significant heterogeneity across workers, firms, and industries, all of which may be insightful into how these channels operate and what the key determinants of knowledge diffusion are. Although we do not explore these extensions in this paper, they would likely be valuable areas of future research.

[48] An important caveat when extrapolating our results to policy changes that would be larger than those considered in our analysis is that the reduced-form nature of our approach limits our ability to assess potential non-linearities in the relationship between NCA enforceability and innovation. We do not claim in this paper that the optimal level of NCA enforceability is zero; rather, we only claim that, on average, the current level of enforceability appears to be too high to maximize innovation. Future research that employs structural models and richer data would allow for a more robust understanding of these trends.

[49] In the case that a state's 2022 enforceability is already less than 0.09, we take that state to zero enforceability for this counterfactual.

7 Conclusion

This paper suggests that NCAs have a significant negative net impact on innovation, in contrast to what is often assumed in policy discussions. The impact is not only statistically significant but also economically significant: a strengthening from the median to the maximum observed enforceability in our sample (i.e., 0.59 to 0.80 on our normalized index) is associated with a 28% decrease in patenting after 5 years. For a more modest change in enforceability, our estimates suggest that an increase of 0.09 points in our normalized index (the mean observed change) would decrease patenting by 14% after 5 years. And these effects become even larger when focusing on high-novelty, high-value patents such as those produced by VC-funded firms.

This effect is not explained by stories about patent screening, changes in firms' propensity to patent, or cross-state spillovers. Moreover, the effect is not driven solely by NCAs restricting entry. Our results show no statistically significant impact on new business applications from changes in NCA enforceability or entrant patenting, and large declines in patenting for incumbent firms. This result could be consistent with a setting where highly enforceable NCAs might simultaneously introduce positive profitability incentives for entry and negative barriers to entry that partially or entirely cancel each other out overall. Given this, entry alone cannot explain the large overall negative effect. Instead, our work here finds significant effects on both incumbent patenting and inventor mobility between firms, with inventor moves declining by 33% in response to stronger NCA enforceability in our sample, and firms becoming more technologically isolated as measured by their citation patterns. These parallel changes in mobility and knowledge flows suggest that labor mobility plays a critical role in innovation by facilitating knowledge diffusion across firms.

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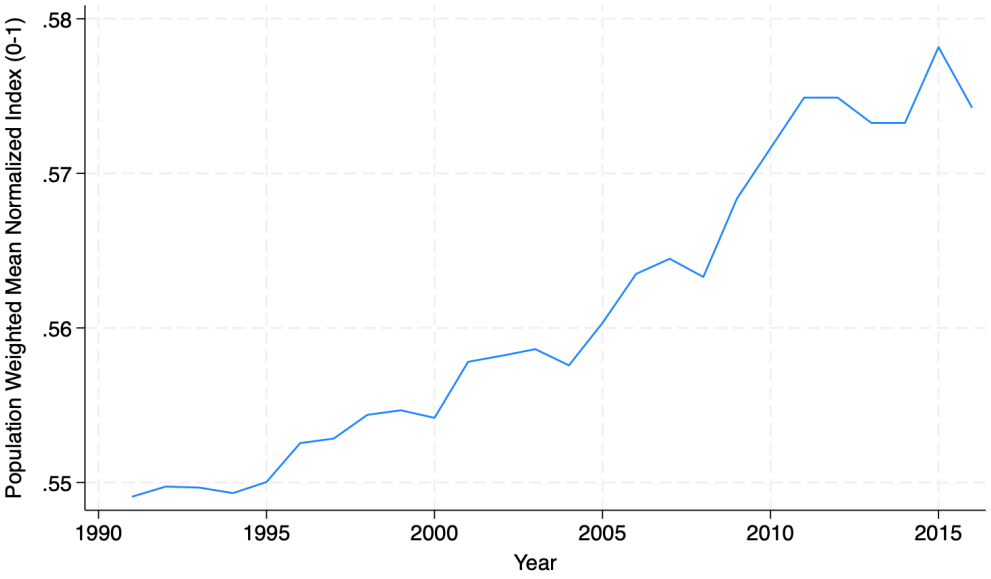
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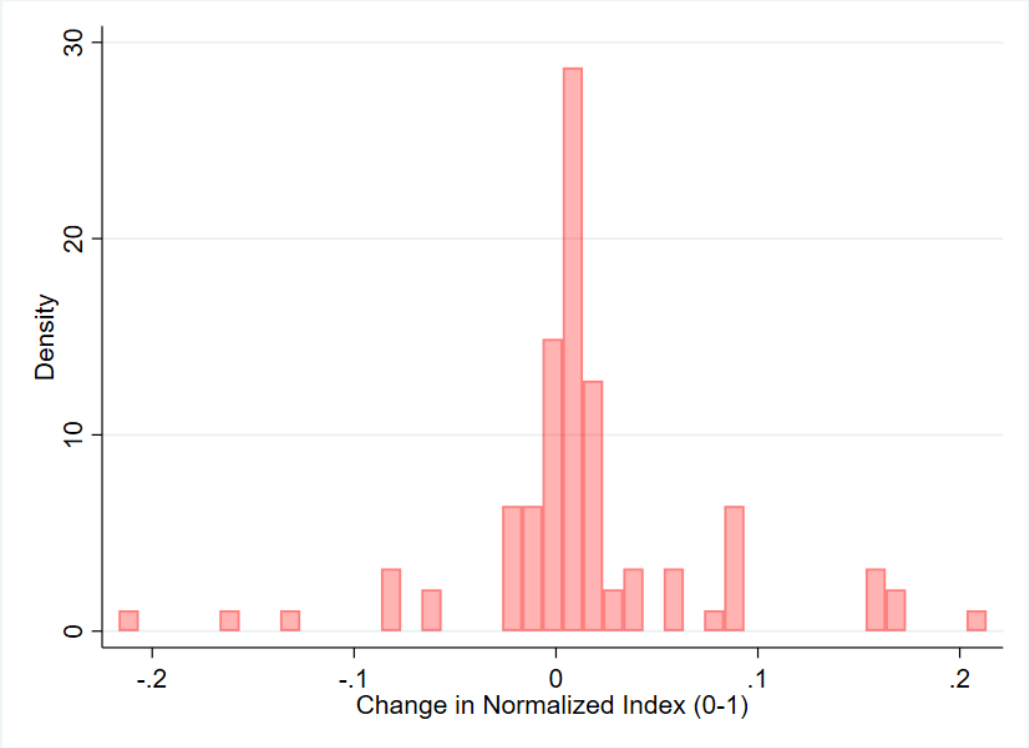
A Supplementary Figures

Figure 1: Trends in NCA Enforceability



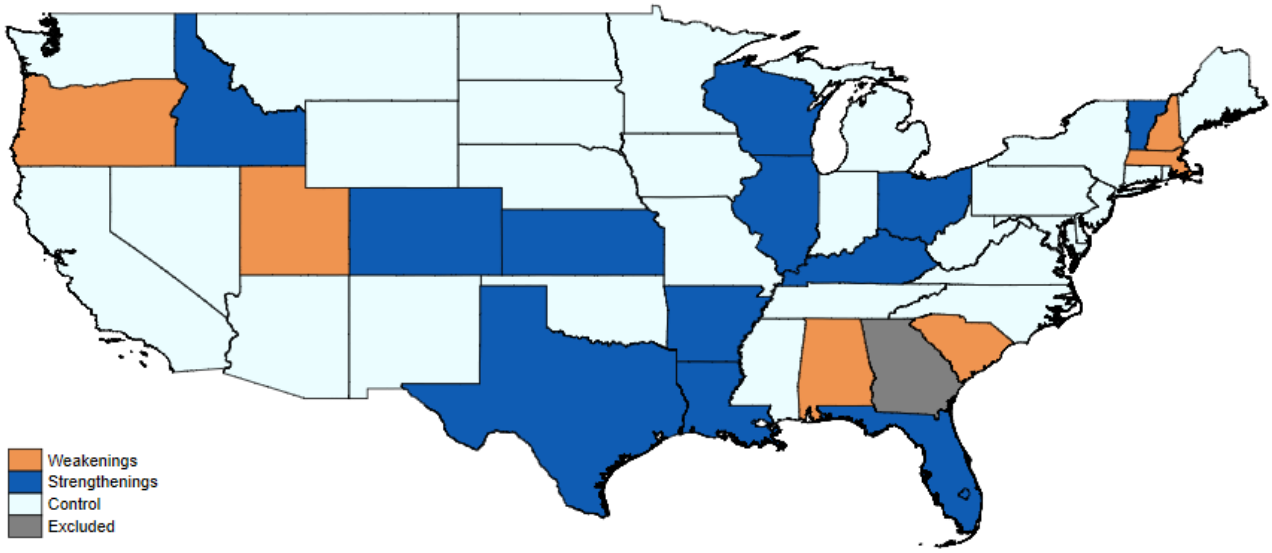
Weighted average state-level NCA enforceability by year. For consistency with the empirical results presented below, states are weighted by share of population in the previous year. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 2: Distribution of Non-Zero Changes in NCA Enforceability



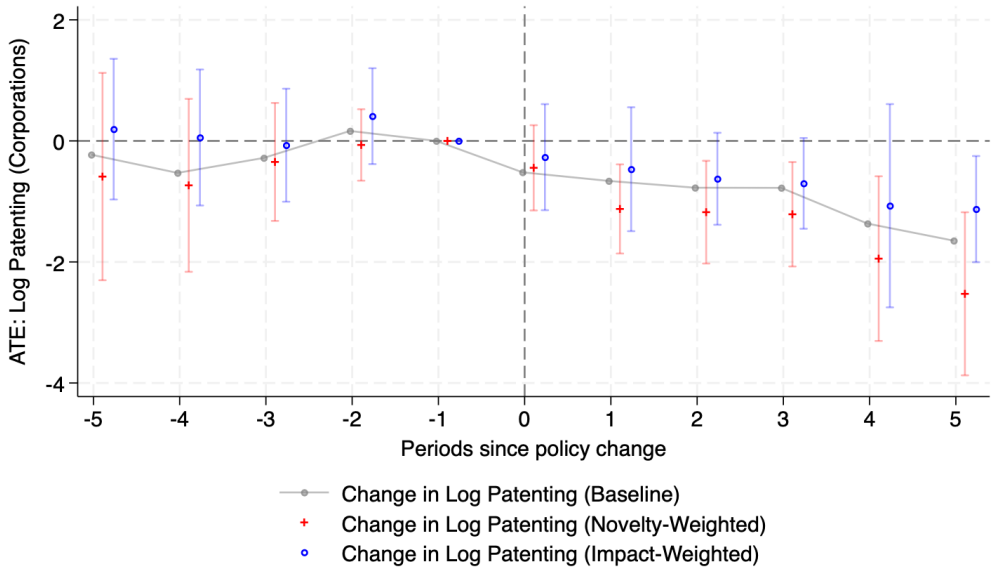
State-level changes in NCA enforceability, as measured by the normalized index, across years. Data sources: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Additional details on the index are available in Appendix Section B.

Figure 3: Map of Baseline Sample



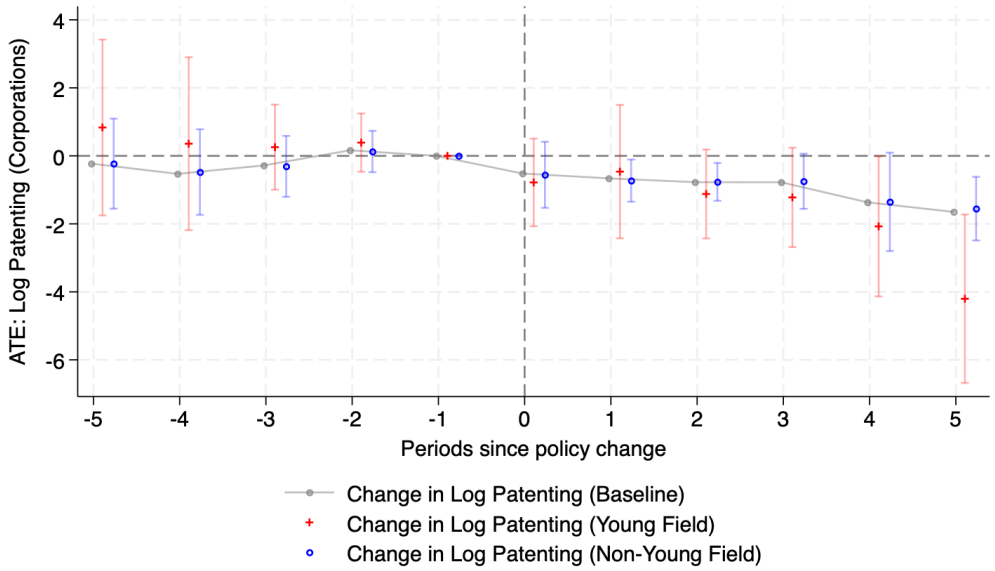
Map of state assignments to treatment and control groups. Note that states listed as treated may also be controls during their not-yet treated period or excluded in subsequent periods (e.g., if another treatment occurs). Data source: Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 4: LP-DiD Coefficient Estimates: Log Impact and Novelty-Weighted Patent Count



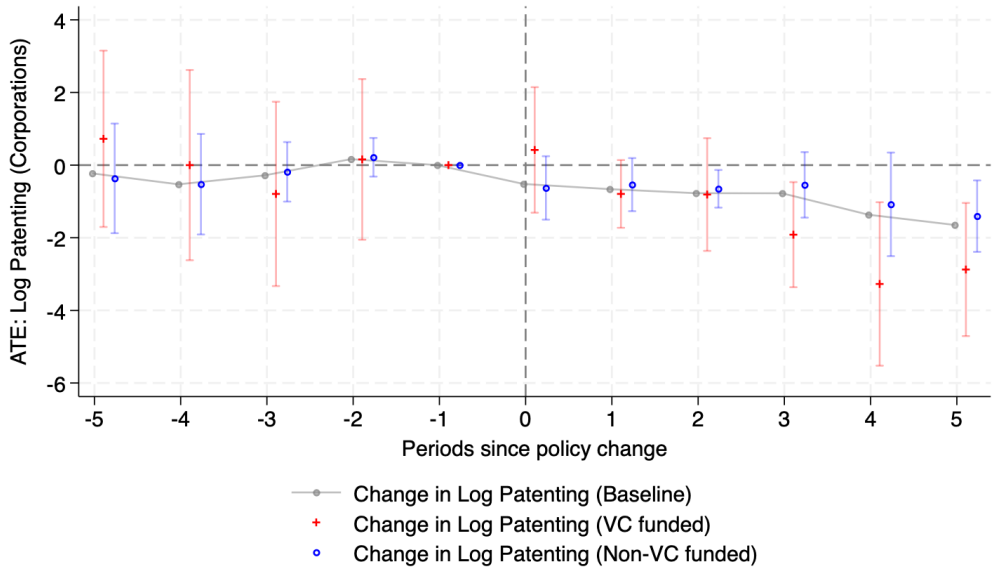
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting weighted by forward citations in year h relative to the time of the policy change ($h = 0$), and weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$). Forward citations measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. Backward citations measure how many previous patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. Inverse backward citations are defined to be equal to $1/(\text{backward cites} + 1)$. Forward and backward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 5: LP-DiD Coefficient Estimates: Log Patent Count – by Field Age



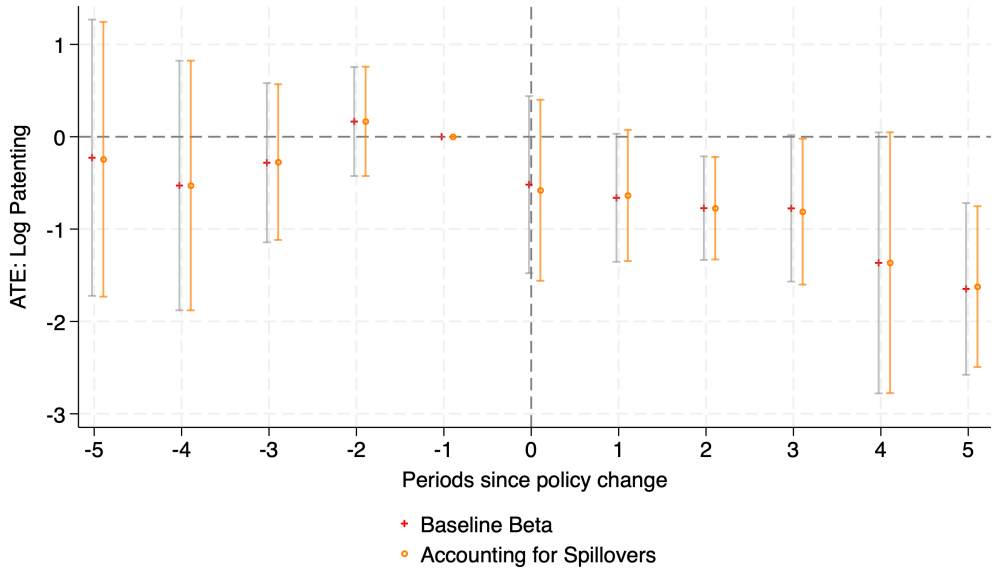
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by the age of the WIPO field. 'Young fields' are those with their first patent after 1970. For patents with multiple WIPO fields, we assign them to the first listed field for the purposes of the estimation. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 6: LP-DiD Coefficient Estimates: Log Patent Count by VC Funding



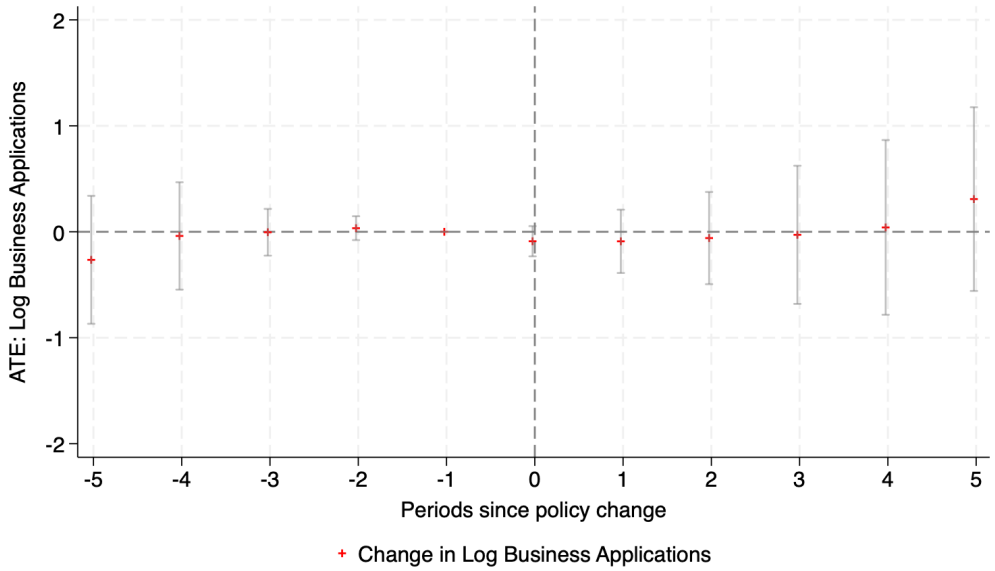
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by firms who received venture capital funding versus those that did not. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; data on patent assignee VC funding compiled by Ewens and Marx (2024). Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 7: Updated Estimated Effect of Changes in NCA Enforceability on Log Patent Count



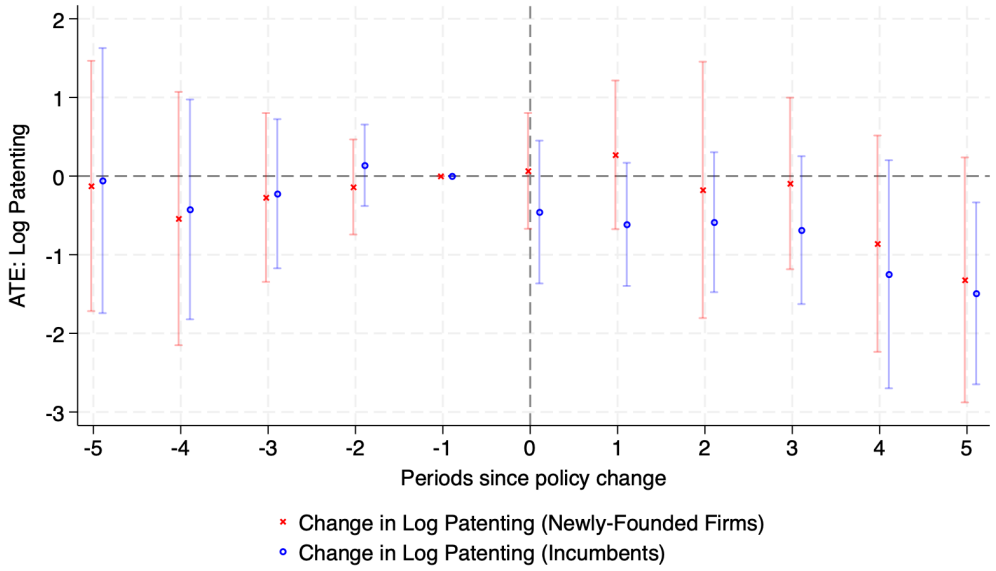
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$) before accounting for spillovers (in red) and after accounting for spillovers (in blue). Details on the econometric specification can be found in Equation 1 (for the red "baseline" series) and in Appendix Equations 2, 3, and 4 immediately above (for the blue "accounting for spillovers" series). Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B. The clean organization lookup is discussed in additional detail in Footnote 46.

Figure 8: Estimated Effect of Changes in NCA Enforceability - Log Entry



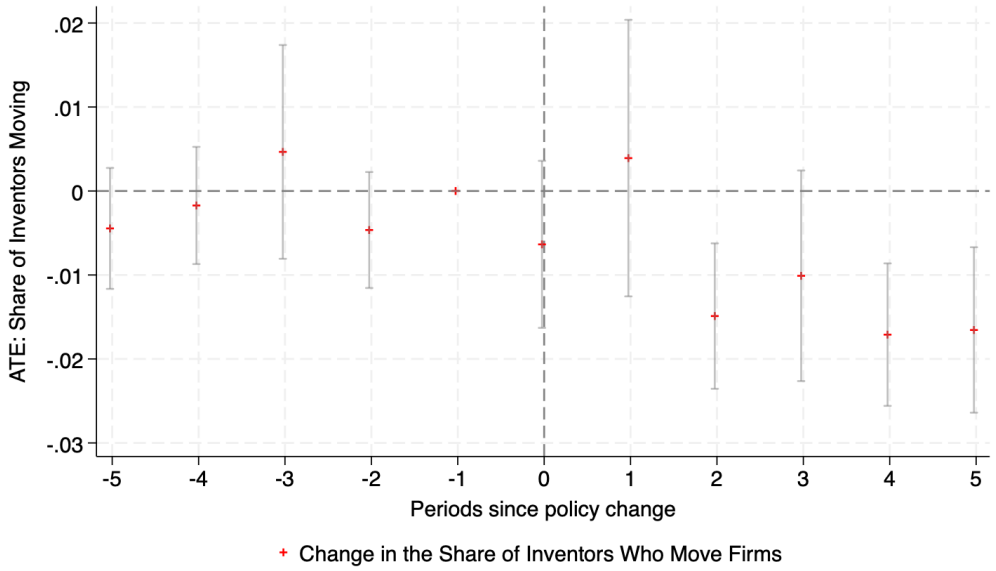
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on log state-level counts of business applications. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the business applications data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 9: Estimated Effect of Changes in NCA Enforceability - Log Patent Count of Newly-Founded Firms, and Log Patent Count of Incumbents



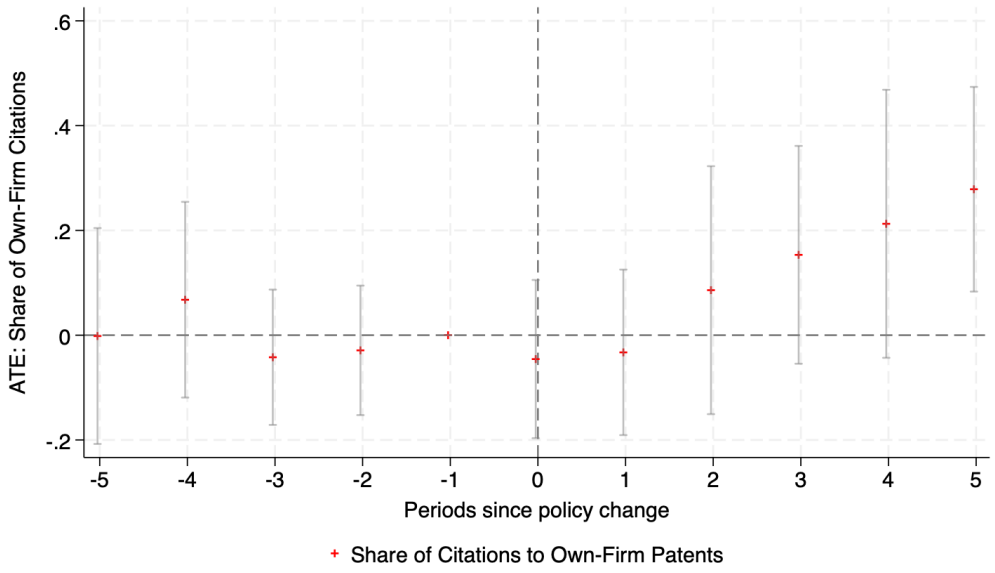
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on log state-level corporate patenting by newly-founded firms, and log state-level corporate patenting by incumbents in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous patenting. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; data on patent assignee founding years compiled by Ewens and Marx (2024); Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the business applications data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 10: Estimated Effect of Changes in NCA Enforceability on Share of Inventors Moving



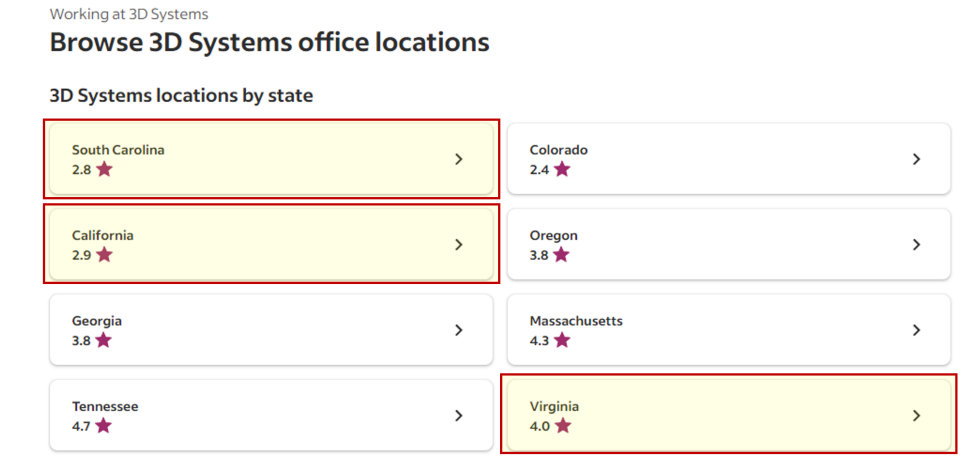
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the share of inventors moving firms in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. Inventor moves are defined as above and now also within state and industry given that these are the types of moves targeted by NCAs. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B. The clean organization lookup is discussed in additional detail in Footnote 46.

Figure 11: Estimated Effect of Changes in NCA Enforceability on Share of Citations to External Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the share of citations that are to patents by other firms. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B. The clean organization lookup is discussed in additional detail in Footnote 46.

Figure 12: Example Assignee Locations



assignee_s~e	organization	new_id	patent_count
CA	3D System, Inc.	383	11
CA	3D Systems, Inc.	383	540
SC	3D Systems, Inc.	383	488
SC	3D Systems, Incorporated	383	7
VA	3D Systems, Incorporated	383	4

Example of a firm with multiple office locations also assigning patents to multiple locations in the patent data both within the same raw organization name(s) and after receiving a clean organization ID from the lookup created by this paper. Data sources: Indeed.com (link); PatentsView; clean organization lookup created by this paper. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 46.

Figure 13: Example Moving Inventor

Year	Inventor ID	Assignee #1	Assignee #2	Assignee #3	Assignee #4
1991	fl:ja_ln:hughett-1	X			
1992	fl:ja_ln:hughett-1	X			
1993	fl:ja_ln:hughett-1	X [Exit]			
1999	fl:ja_ln:hughett-1		X [Enter]		
2000	fl:ja_ln:hughett-1		X		
2003	fl:ja_ln:hughett-1		X [Exit]	X [Enter/Exit]	
2005	fl:ja_ln:hughett-1				X [Enter]
2008	fl:ja_ln:hughett-1				
2009	fl:ja_ln:hughett-1				X
2010	fl:ja_ln:hughett-1				X
2011	fl:ja_ln:hughett-1				X
2012	fl:ja_ln:hughett-1				X
2013	fl:ja_ln:hughett-1				X
2014	fl:ja_ln:hughett-1				X
2016	fl:ja_ln:hughett-1				X

Example of an inventor switching between patenting at different firms over time. Data source: PatentsView. Details on the patent data are available in Section 2.2.

B Bishara (2011) Index Questions

1. Is there a state statute of general application that governs the enforceability of covenants not to compete? (Weight = 10)
   - Score = 0: statute that disfavors enforcement
   - Score = 5: no statute or statute that is neutral in its approach to enforcement
   - Score = 10: statute that favors strong enforcement

2. What is an employer's protectable interest and how is that defined? (Weight = 10)
   - Score = 0: strictly defined limited protectable interest
   - Score = 5: balanced approach to defining a protectable interest
   - Score = 10: broadly defined protectable interest

3. What must plaintiff be able to show to prove the existence of an enforceable covenant not to compete? (Weight = 5)

- Score = 0: strong burden of proof on the employer
- Score = 5: balanced approach to the burden placed on the employer
- Score = 10: weak burden of proof on the plaintiff employer

4. Does the signing of a covenant not to compete at the inception of the employment relationship provide sufficient consideration to support the covenant? (Weight = 10)

   - Score = 0: start of employment is never sufficient
   - Score = 5: start of employment is sometimes sufficient
   - Score = 10: start of employment is always sufficient

5. Will a change in the terms and conditions of employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun? Will continued employment provide sufficient consideration after the employment relationship has begun? (Weight = 5)

   - Score = 0: neither continued employment nor a beneficial change in terms would be sufficient consideration
   - Score = 5: only a beneficial change in terms was sufficient to support a covenant not to compete
   - Score = 10: continued employment is always sufficient

6. If the restrictions in the covenant not to compete are unenforceable because they are overbroad, are the courts permitted to modify the covenant to make the restrictions more narrow and to make the covenant enforceable? If so, under what circumstances will the courts allow reduction and in what form? (Weight = 10)

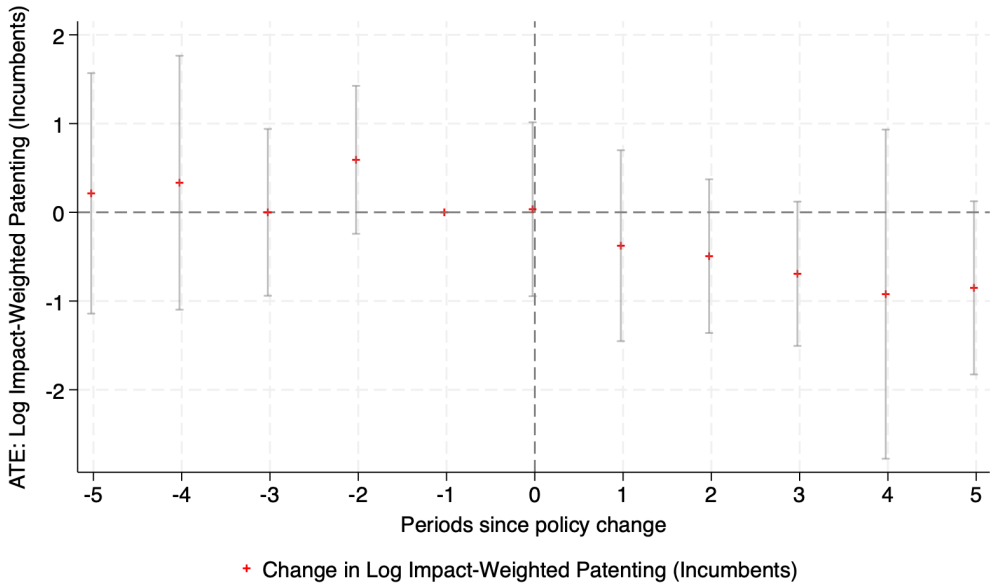
   - Score = 0: strictly defined limited protectable interest
   - Score = 5: balanced approach to defining a protectable interest
   - Score = 10: broadly defined protectable interest

7. If the employer terminates the employment relationship, is the covenant enforceable? (Weight = 10)

   - Score = 0: not enforceable if the employer terminates
   - Score = 5: enforceable only in some circumstances
   - Score = 10: always enforceable if the employer terminates

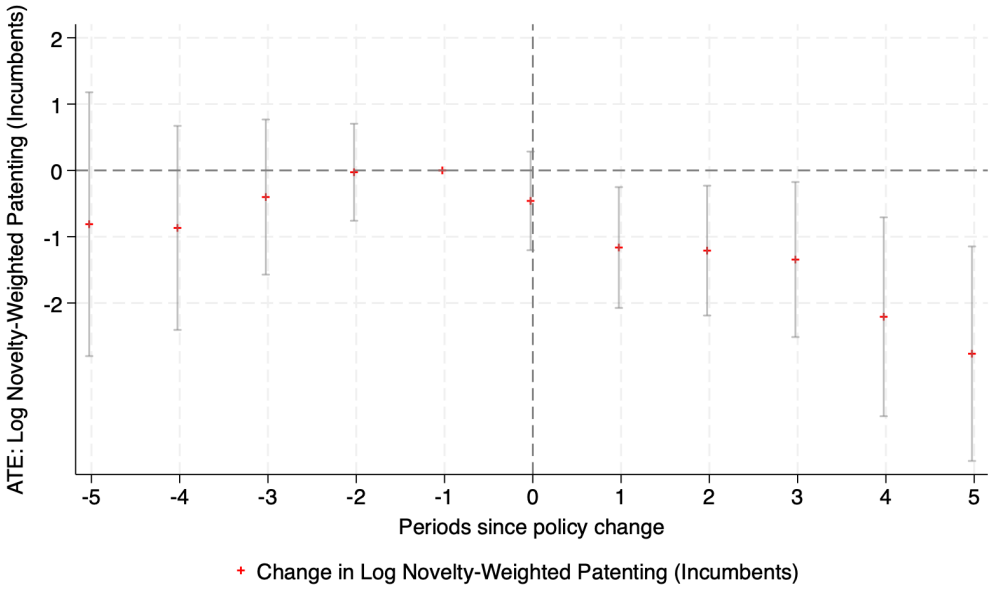
C Additional Results

Figure 14: LP-DiD Coefficient Estimates: Log Impact-Weighted Patent Count - Incumbents Only



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by forward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous observed patenting. Forward citations measure how many subsequent patents cite the patent in question and therefore are thought to approximate the extent to which a given patent has led to follow-on inventions. However, we de-prioritize them in this analysis because of the potential for NCAs to affect not only patenting but also citation networks. Forward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 15: LP-DiD Coefficient Estimates: Log Novelty-Weighted Patent Count - Incumbents Only

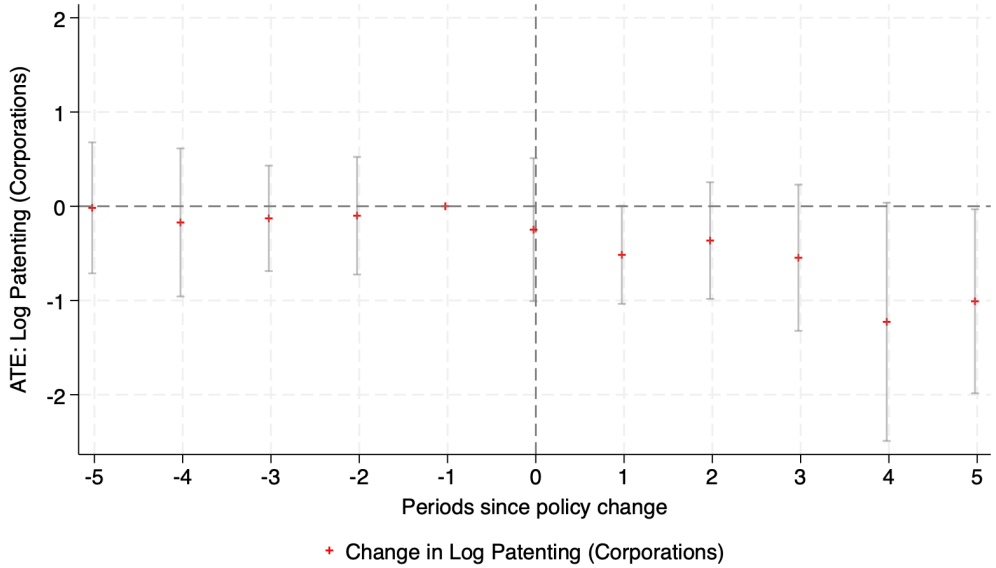


Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as corporations with previous observed patenting. Backward citations measure how many previous patents were cited by the patent in question, with the intuition that having fewer backward citations indicates a more original invention. Inverse backward citations are defined to be equal to 1/(backward cites + 1). Backward citations are windsorized at the 1st and 99th percentiles. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

D Robustness Checks

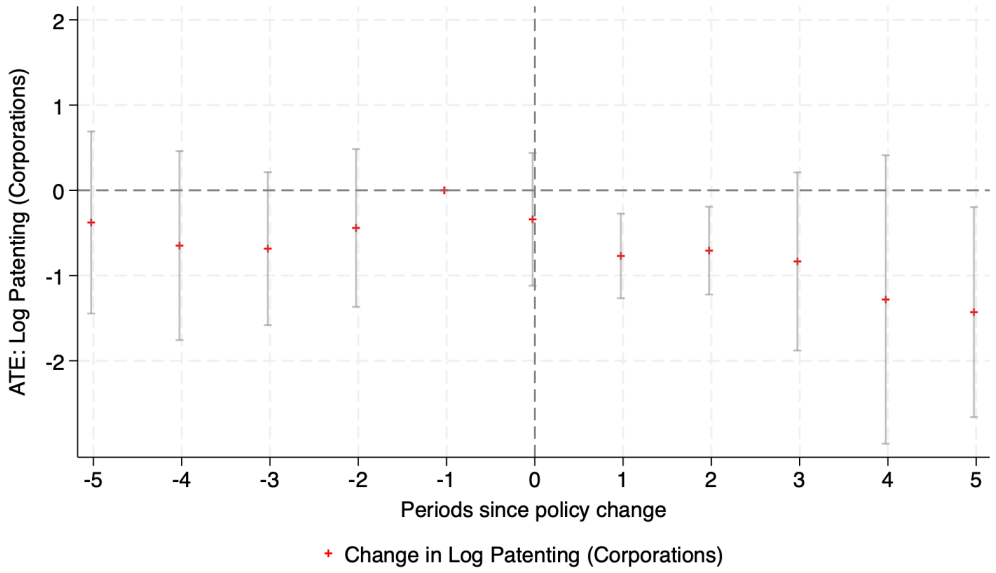
D.1 Alternate Patent Location Definition

Figure 16: LP-DiD Coefficient Estimates: Log Patent Count - Inventor Location



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Uses the location of the first-listed inventor rather than the location of the assignee as the location of the patent. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 17: LP-DiD Coefficient Estimates: Log Patent Count - Shared Location



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Uses the shared location of the first-listed inventor and assignee as the location of the patent. Excludes patents with different inventor and assignee locations. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

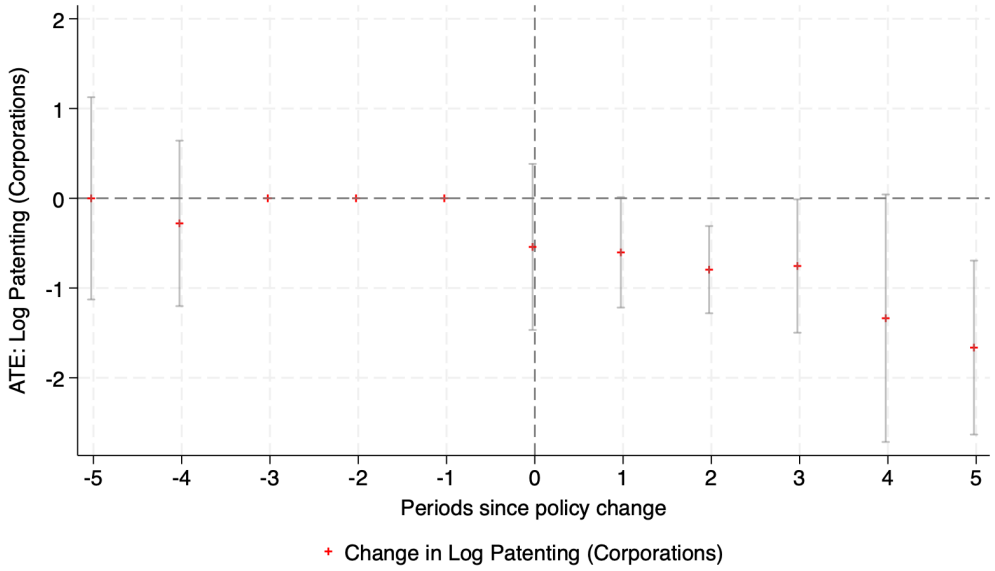
D.2 Example Results with Outcome Lags in LP-DiD

As discussed in Dube et al. (2023), we can also include outcome lags on the right-hand side of the estimating equation to control for pre-treatment values of time-varying covariates:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} \quad & \text{treatment (change in index)} \\ + \sum_{k=1}^{K} \gamma_k^h \cdot y_{i,t-k} \quad & \text{outcome lags} \\ + \delta_{t+h} - \delta_{t-1} \quad & \text{time effects} \\ + \epsilon_{i,t+h} \quad & \text{for } h = -H, ..., H, \end{aligned} \tag{1}$$

where we include K lags of the outcome variable to help control for any concerns about patenting predicting changes in enforceability. Doing so gives very similar results for our patent outcomes (see below).

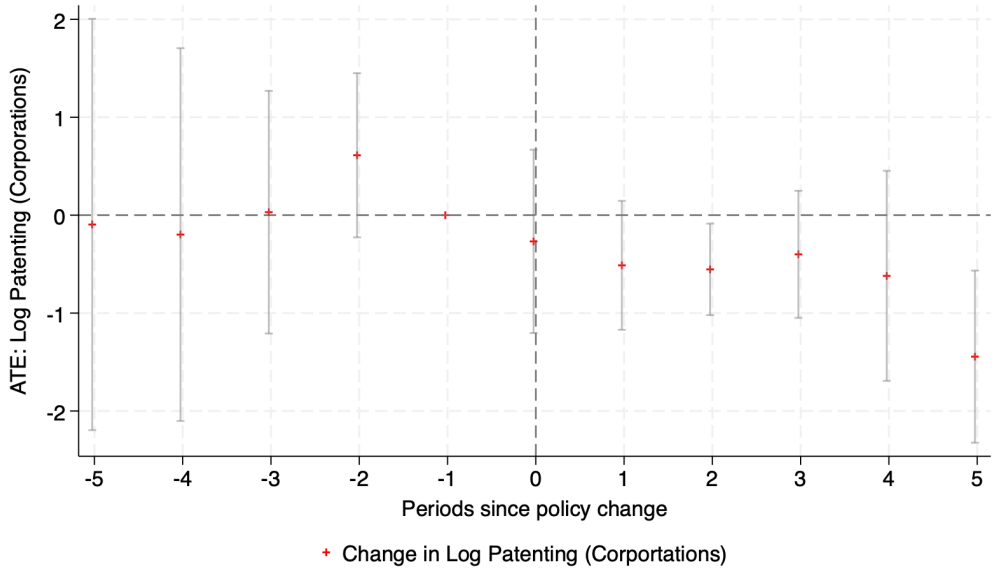
Figure 18: LP-DiD Coefficient Estimates: Log Patent Count - Conditioning on Lagged Outcomes



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Appendix Equation 1 immediately above. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$, $H = 5$, and $K = 3$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

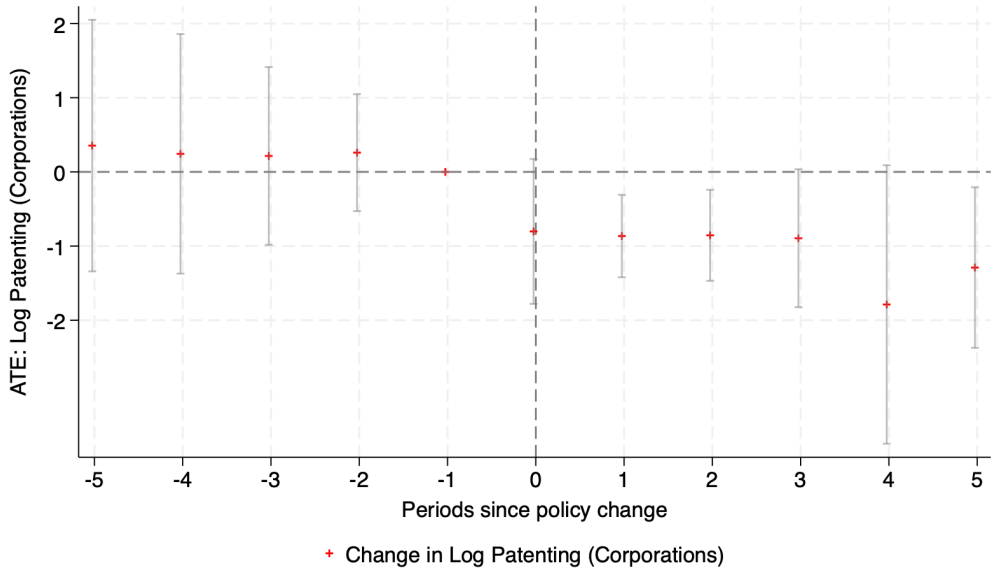
D.3 Example Results with Alternate Weighting

Figure 19: LP-DiD Coefficient Estimates: Log Patent Count - Unweighted



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are not weighted. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

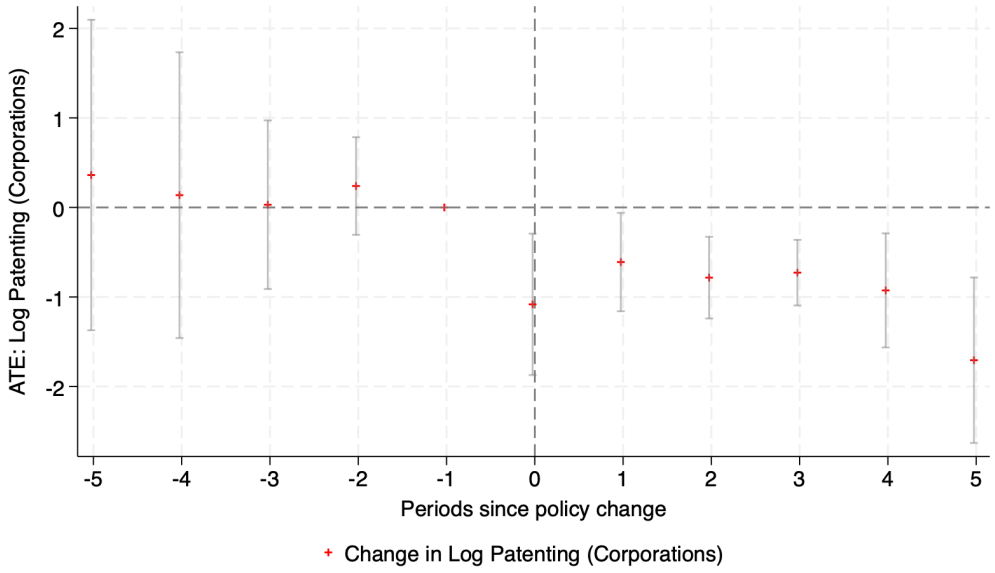
Figure 20: LP-DiD Coefficient Estimates: Log Patent Count - Weighted by Share of Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of patent applications filed in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

D.4 Results with Balanced Panel

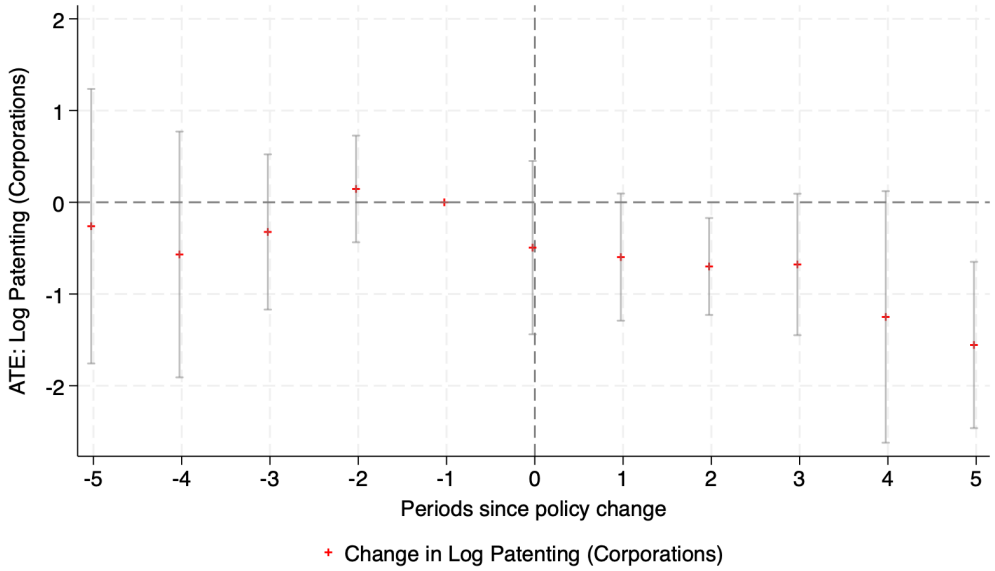
Figure 21: LP-DiD Coefficient Estimates: Balanced Panel



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Limited to a balanced panel where we can observe a full clean 5 years of outcomes on either side of t. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

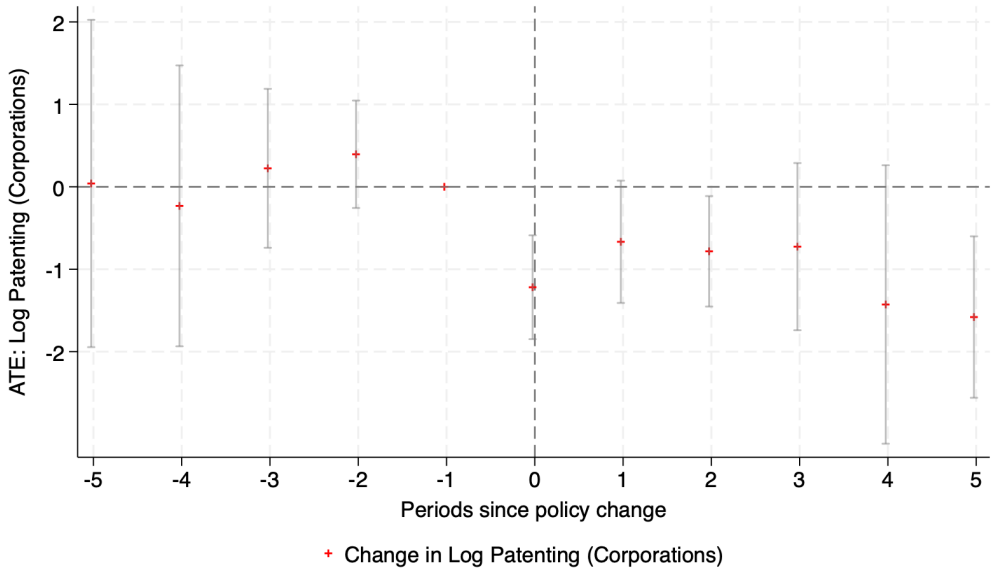
D.5 Alternative Sample Definitions

Figure 22: LP-DiD Coefficient Estimates: Log Patent Count - Excluding California



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Excludes California from the analysis. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

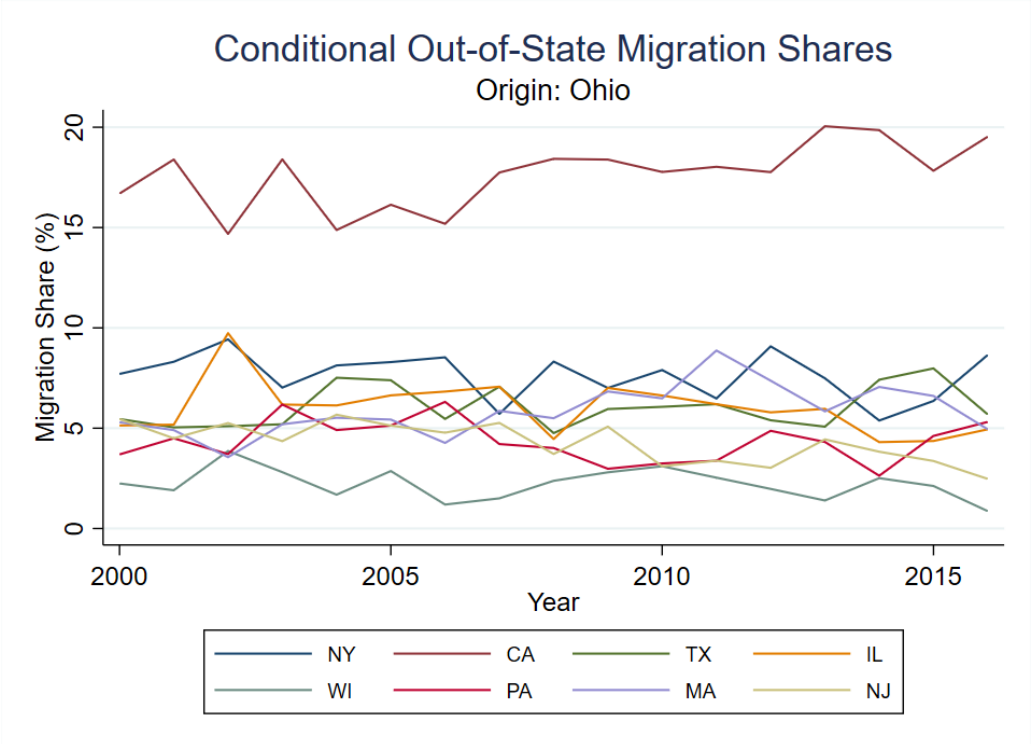
Figure 23: LP-DiD Coefficient Estimates: Log Patent Count - Strengthenings Only



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$). Excludes treatments that are weakenings (i.e., decreases in enforceability) from the analysis. Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B.

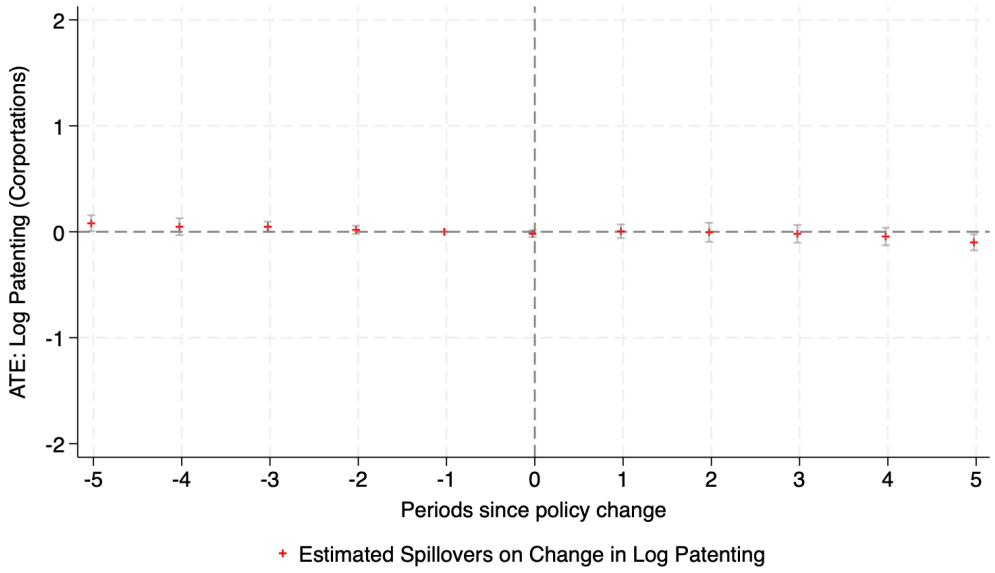
D.6 Accounting for Spillovers

Figure 24: Mover Destination Stability (Ohio)



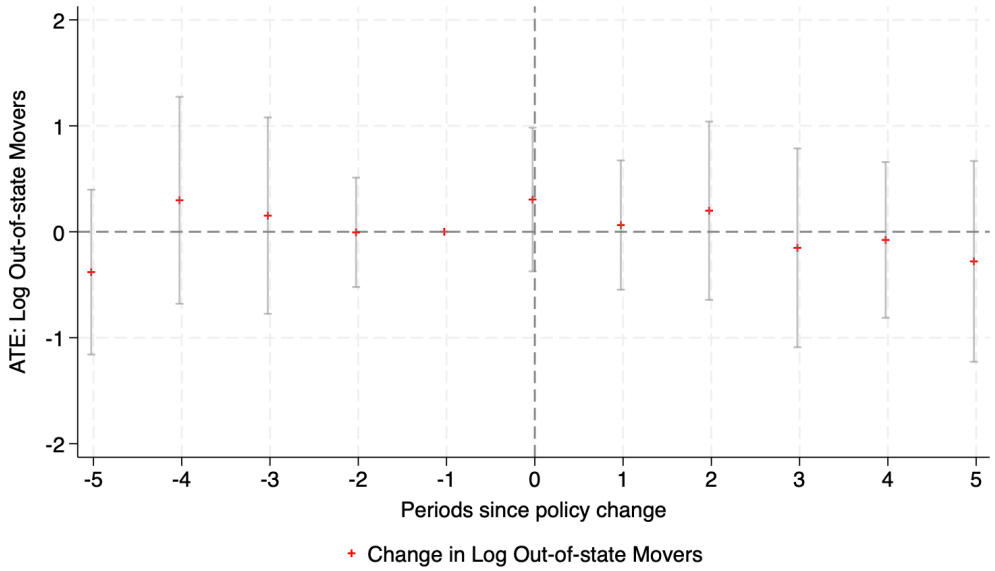
Plot of the annual share of Ohio inventors who move out of state who end up in the destination states denoted in the legend. For visibility, only the 8 most common destination states are plotted. Inventor moves are defined as above. Data sources: PatentsView; clean organization lookup. Details on the patent data are available in Section 2.2. The clean organization lookup is discussed in additional detail in Footnote 46.

Figure 25: Estimated ρ



Plot of the estimated average treatment effect of a 1 percent increase in the number of inventors in a destination state because of changes in NCA enforceability in other origin states on the log of destination state-level corporate patenting in year h relative to the time of the destination state's policy change ($h = 0$). Details on the econometric specification can be found in Equations 2, 3, and 4 above. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B. The clean organization lookup is discussed in additional detail in Footnote 46.

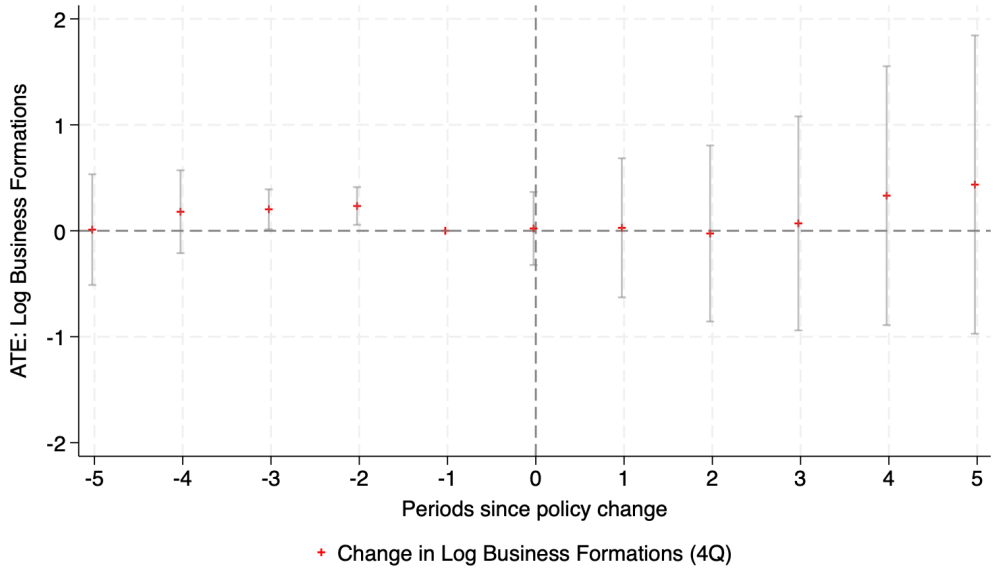
Figure 26: First Stage Results of Spillovers Regression



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of out-of-state movers in year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 3. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates; clean organization lookup. Details on the patent data are available in Section 2.2. Details on the index are available in Section 2.1 and Appendix Section B. The clean organization lookup is discussed in additional detail in Footnote 46.

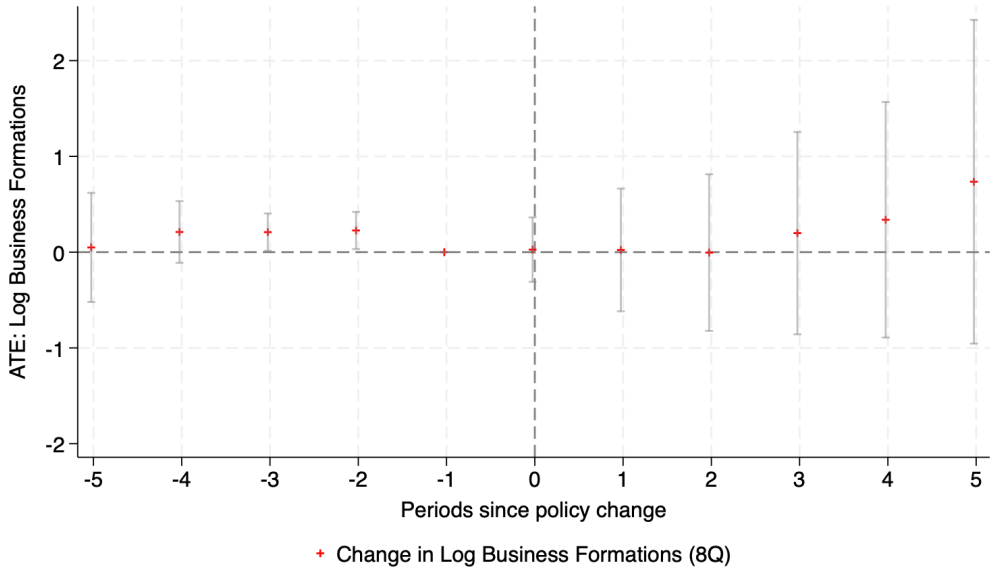
D.7 Entry Robustness Checks

Figure 27: LP-DiD Coefficient Estimates: Log Entry (Four-Quarter Business Formations)



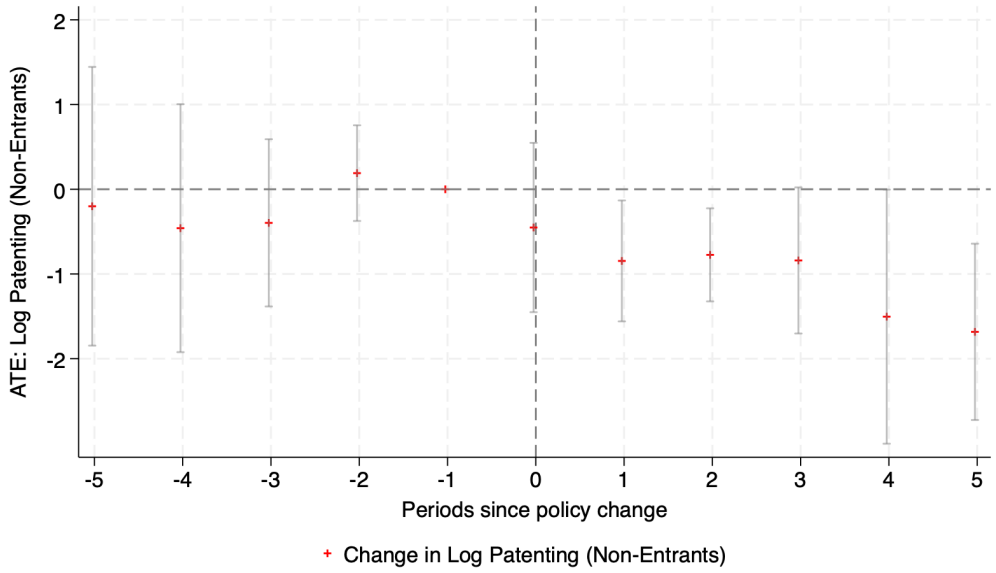
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business formations within four quarters of the year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the business formations data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 28: LP-DiD Coefficient Estimates: Log Entry (Eight-Quarter Business Formations)



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business formations within eight quarters of the year h relative to the time of the policy change ($h = 0$). Details on the econometric specification can be found in Equation 1. Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: Census BFS; Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the business formations data are available in Section 2.3. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 29: LP-DiD Coefficient Estimates: Log Patent Count – Non-Newly-Founded Firms



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by non-newly-founded firms in year h relative to the time of the policy change ($h = 0$). Error bars show 95% confidence intervals. Standard errors are clustered at state level. States are weighted by share of population in the previous year. We specify $c = 15/600$ and $H = 5$. Data sources: PatentsView; data on patent assignee founding years compiled by Ewens and Marx (2024); Bishara (2011) index that summarizes NCA enforceability by state, as expanded by Marx (2022) and this paper, normalized to be [0,1] rather than [0,600]; Census Bureau's Annual Population Estimates. Details on the index are available in Section 2.1 and Appendix Section B.