

Online Appendix

Innovation through Inventor Mobility: Evidence from Non-Compete Agreements

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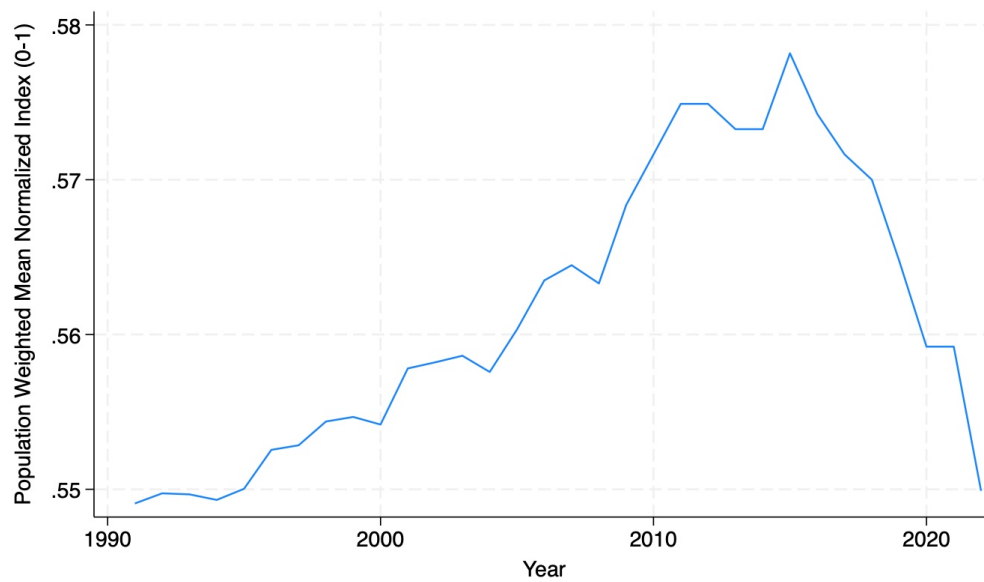
A Supplementary Figures

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Median	Max
NCA Enforceability	0.62	0.11	0.39	0.64	0.80
State Population (millions)	6.07	5.60	0.62	4.53	23.36
Number of Inventors	1643.35	3131.72	12.00	359.50	12762.00
Patent Count	1220.70	1732.13	21.00	614.00	6679.00
VC Patent Share (%)	8.48	5.69	0.69	8.37	18.56
Young Field Patent Share (%)	6.89	7.72	2.42	4.86	38.54
Incumbent Patent Share (%)	73.62	15.77	38.10	79.40	96.47
Business Applications	45689.15	48672.80	4523.00	32436.00	187555.00
Share Inventors Moving (%)	0.24	0.37	0.00	0.00	1.30
Share Same Firm Citations (%)	13.47	4.39	5.11	12.51	25.63

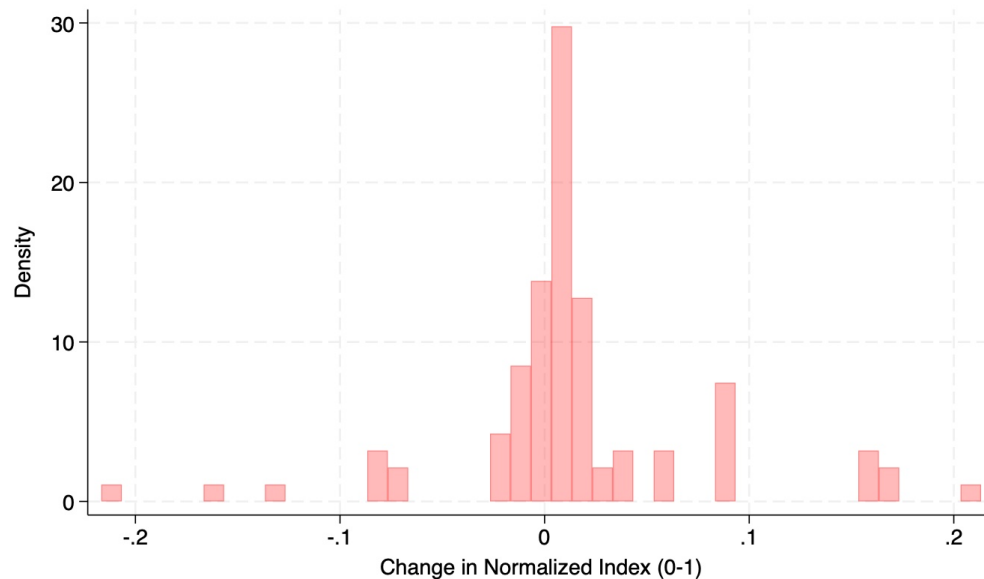
Notes: All statistics are state-level averages over 1991-2016. Data sources: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0, 1]$ rather than $[0, 600]$; US Census Bureau (2022a); US Census Bureau (2022b).

Figure 1: Trends in NCA Enforceability



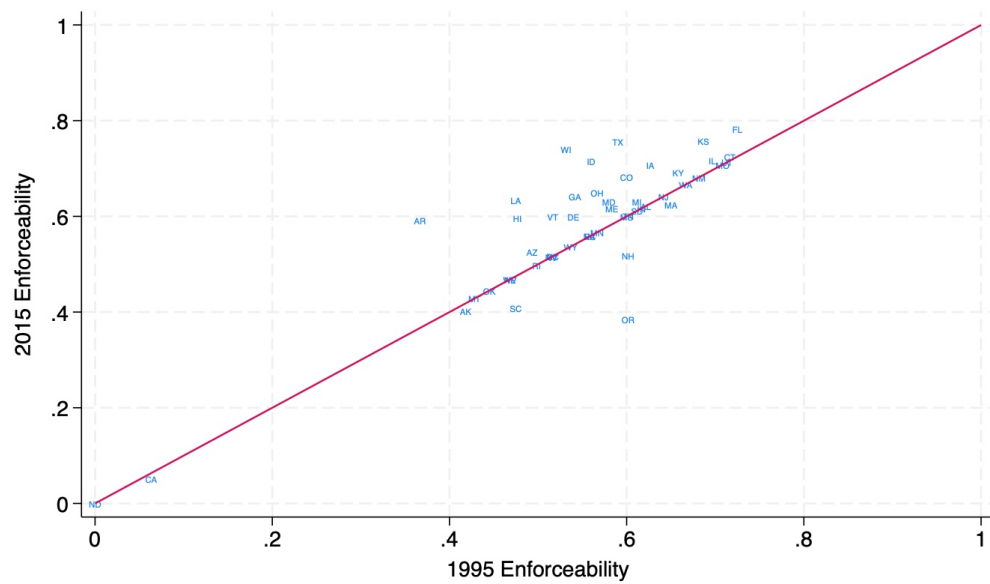
Weighted average state-level NCA enforceability by year. For consistency with the empirical results presented below, states are weighted by share of population in the previous year. Data sources: Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau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

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



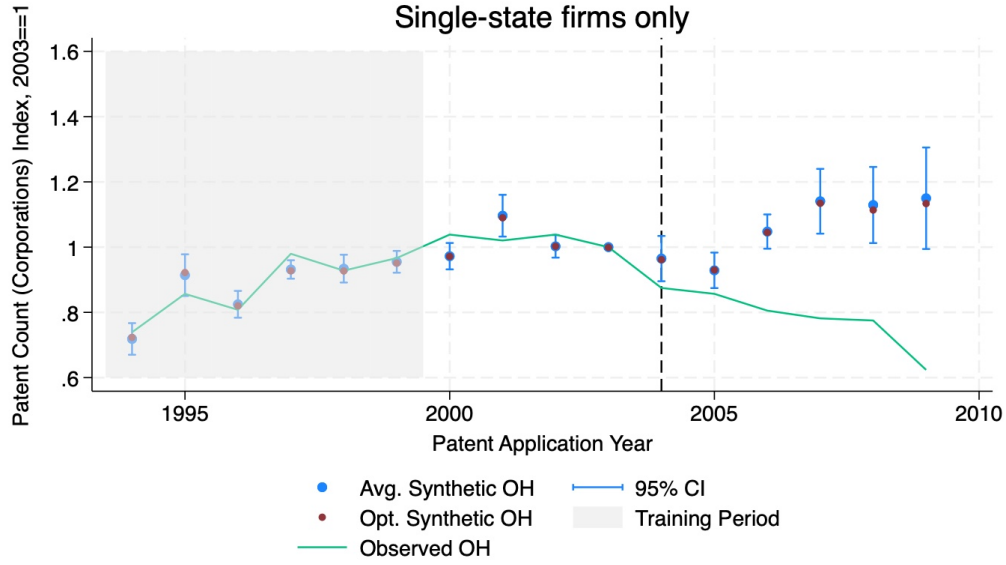
State-level changes in NCA enforceability, as measured by the normalized index, across years. Data sources: Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$. Additional details on the index are available in Appendix Section B.

Figure 3: Comparison Between State-Level NCA Enforceability in 1995 and 2015



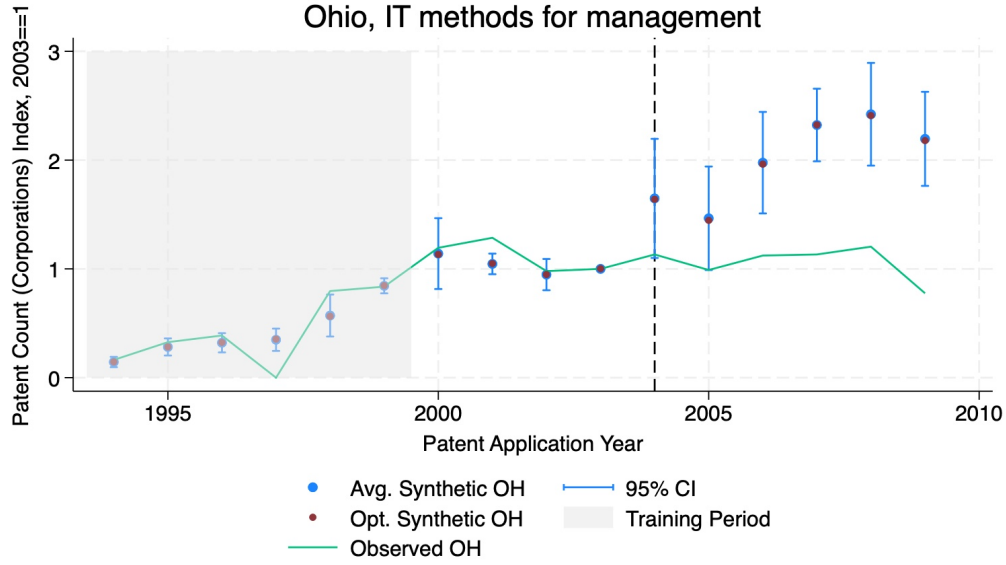
State-level NCA enforceability, as measured by the normalized index in the specified year. Red 45-degree line represents no change. Data sources: Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$. Additional details on the index are available in Appendix Section B.

Figure 4: Ohio Patenting – Synthetic Control Comparison, Single-State Assignees



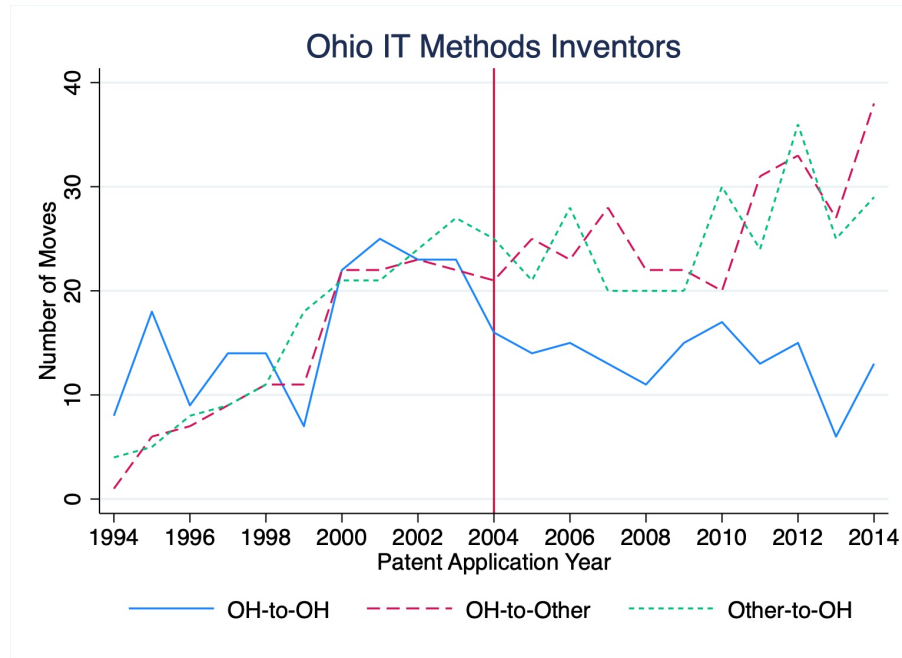
Comparison of observed Ohio patenting to synthetic Ohio patenting, limited to firms who only patent in a single state. The green line visualizes the trend in observed Ohio patenting. The red dots show the optimal synthetic control when all never-treated states are included as potential controls. The *synth* command in Stata constructs optimal weighted combination of untreated units in the training period as: 12% Virginia, 7% District of Columbia, 7% Mississippi, 7% Nebraska, 7% Missouri, 7% North Carolina, 6% Minnesota, 6% Rhode Island, 6% New Hampshire, 6% Alabama, 6% New Jersey, 6% Pennsylvania, 5% Tennessee, 5% West Virginia, 5% South Dakota, and 3% Indiana (rounded weights may sum to more than 100%). 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: USPTO (2016). Details on the patent data are available in Section 2.2.

Figure 5: 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 (rounded weights may sum to more than 100%). 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: USPTO (2016). Details on the patent data are available in Section 2.2.

Figure 6: 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: USPTO (2016); 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 51.

[illegible]

Legend:

- Weakenings
- Strengthenings
- Control
- Combination

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Legend:

- Weakenings
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- Control
- Combination

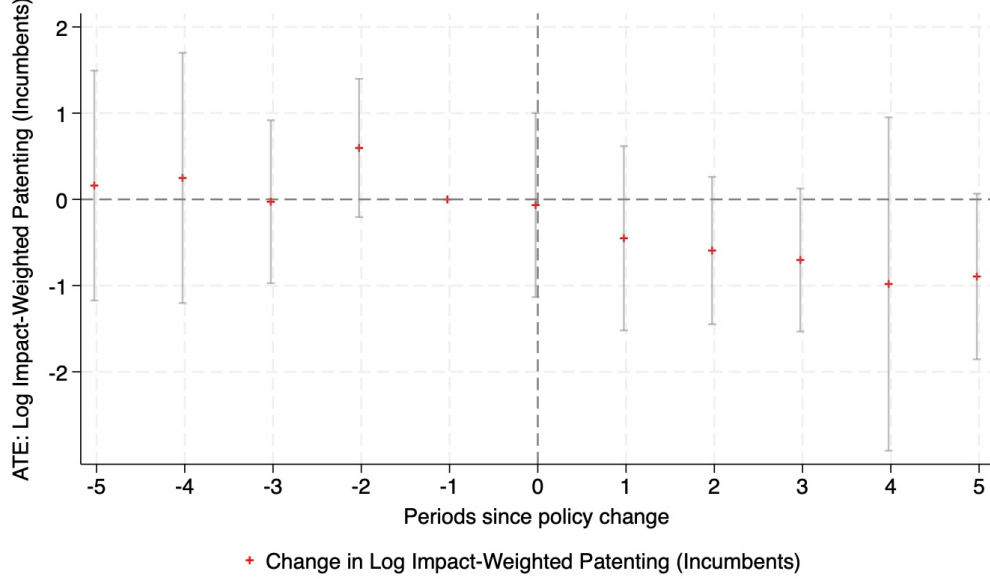
B Bishara (2011) Index Questions

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: neither blue pencil nor judicial modification is allowed
 - Score = 5: blue pencil modifications are allowed as a way to reform the contract instead of disallowing it outright
 - Score = 10: judicial modification is allowed and there are broad circumstances where revisions can be made and limited restrictions on maximum enforcement
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

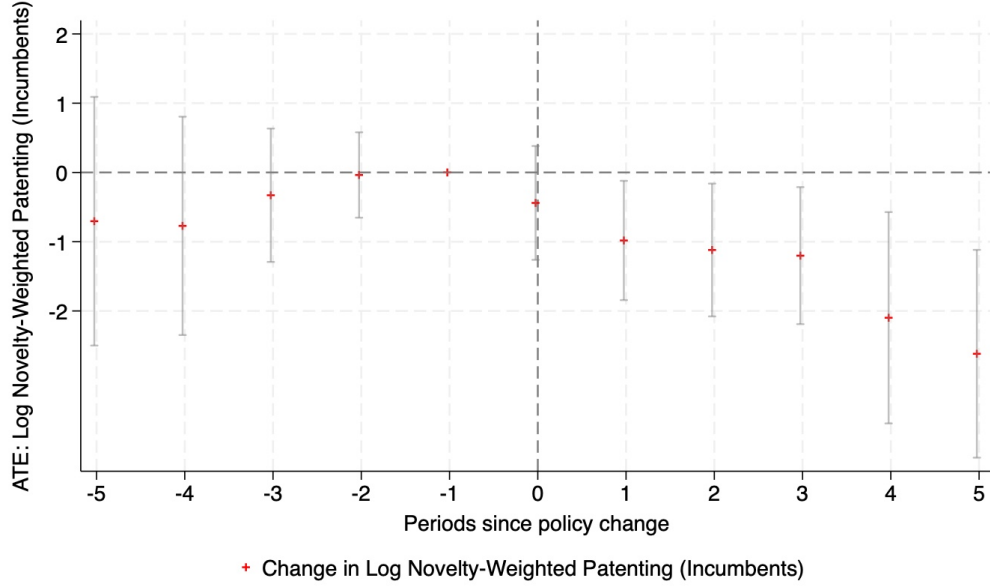
C Additional Results

Figure 9: LP-DiD Coefficient Estimates: Log Impact-Weighted Patent Count - Incumbents Only



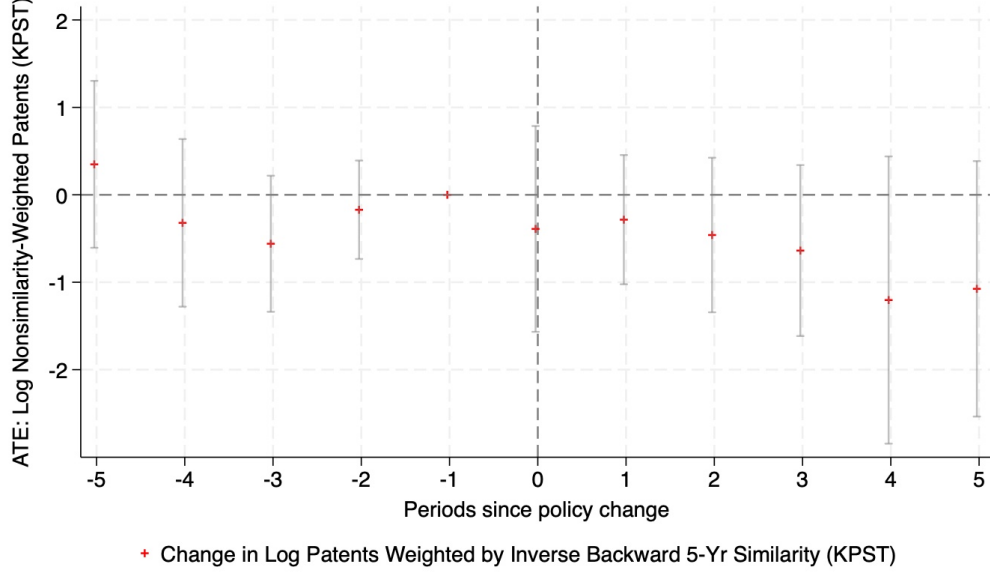
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by forward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are defined as 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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 10: LP-DiD Coefficient Estimates: Log Novelty-Weighted Patent Count - Incumbents Only



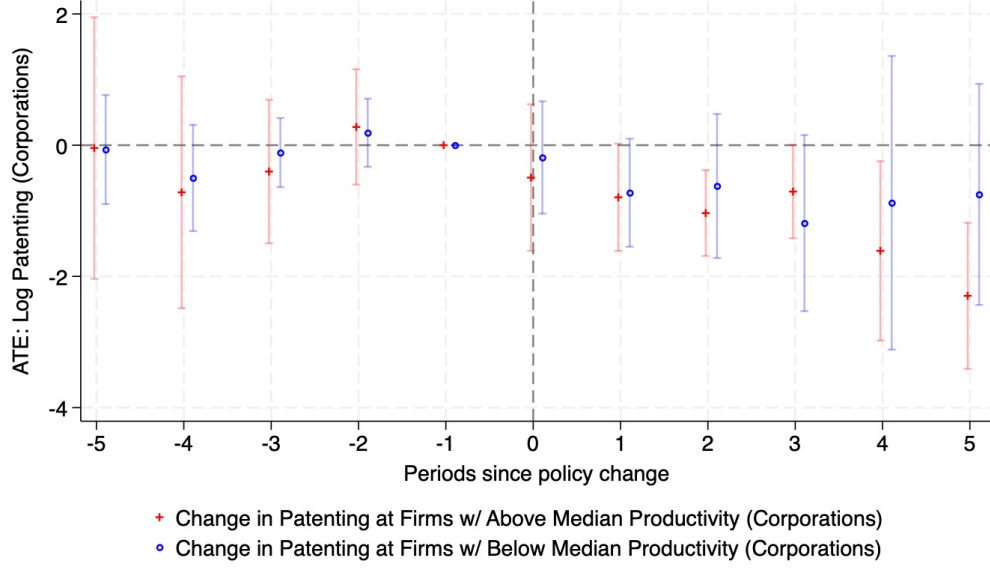
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting by incumbents weighted by inverse backward citations in year h relative to the time of the policy change ($h = 0$). Incumbents are 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 $1/(\text{backward cites} + 1)$. 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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 11: LP-DiD Coefficient Estimates: Log Nonsimilarity-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 inverse backward 5-year aggregate patent similarity in year h relative to the time of the policy change ($h = 0$). Backward 5-year aggregate patent similarity comes from Kelly et al. (2021), and the inverse is defined to be equal to $1/(\text{backward similarity})$. 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: USPTO (2016); Kelly et al. (2021); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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 12: LP-DiD Coefficient Estimates: Log Patent Count - Split by Assignee Productivity

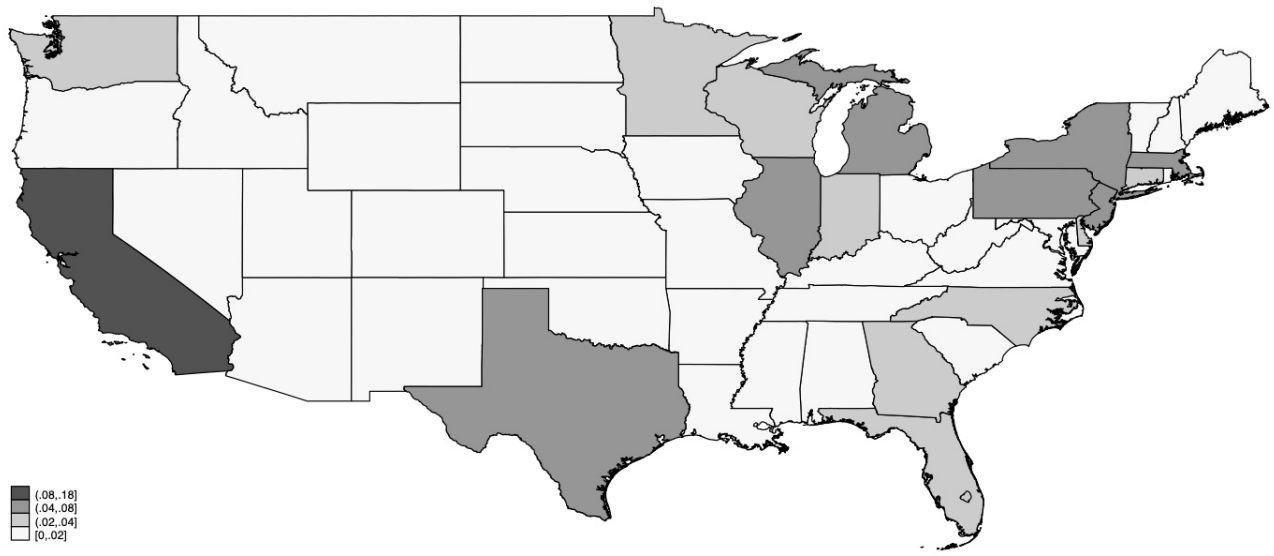


Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the state-level log corporate patent, split into assignee-years with average productivity (in terms of patents per inventor) above the median across assignees in that year and below the median. 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the index are available in Section 2.1 and Appendix Section B.

C.1 Two-Stage Cross-State Spillovers Analysis

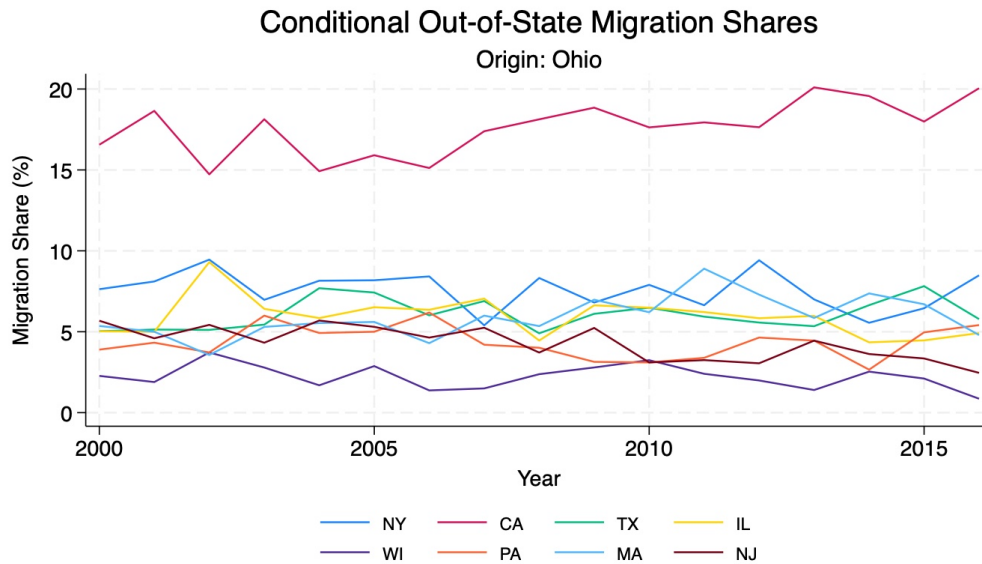
Inventor migration patterns have stable determinants (e.g., distance, industry mix, demographics, and relative economy size). For example, **Appendix Figure 13** shows the relative shares with which inventors moving out of Ohio end up in other states. California is the most common, as might be expected 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 14** shows that these migration shares (conditional on out-of-state migration) are relatively constant over time.

Figure 13: 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: USPTO (2016); 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 51.

Figure 14: 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: USPTO (2016); 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 51.

Given this, we can define a gravity-style control for the cumulative exposure of state i to all other states' changes in enforceability.⁶⁰ 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:

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

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:⁶¹

$$1. \quad M_{o,t+h} - M_{o,t-1} = \theta_h \cdot \mathbb{I}_{o,t} \cdot \Delta X_{o,t} + \gamma_{t+h} - \gamma_{t-1} + \varepsilon_{o,t+h}^1 \quad (2)$$

$$2. \quad y_{i,t+h} - y_{i,t-1} = \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} + \delta_{t+h} - \delta_{t-1} + \rho_h \cdot \hat{\lambda}_{i,t+h} + \varepsilon_{i,t+h}^2 \quad (3)$$

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

This analysis suggests that there are no statistically significant cross-state spillover effects from migration.⁶² 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 15**). This result is driven by the lack of any statistically significant impact of changes in NCA enforceability on out-of-state moves in the first stage of this regression analysis, with F-statistic of the treatment indicators between 0 and 3 in all years.⁶³ Accordingly, **Appendix Figure 16** shows that the treatment effects estimated after correcting for cross-state spillovers are essentially identical to those from our baseline specification.⁶⁴

⁶⁰This control is in the style of existing work such as Dubé et al. (2017); Borusyak and Hull (2023); Borusyak et al. (2022); 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.

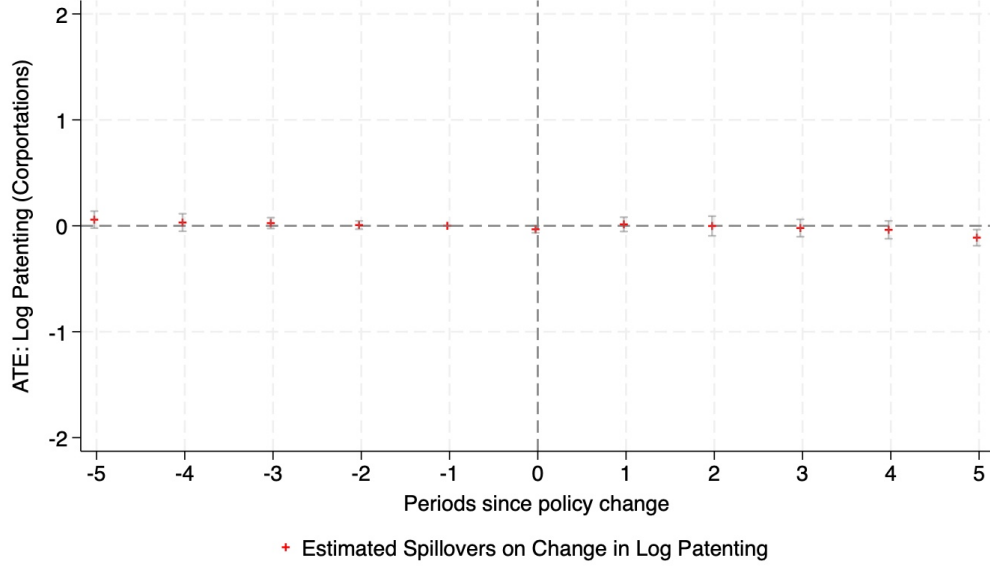
⁶¹The two identifying assumptions necessary for this approach are: (i) treatment in state i affects state j patenting only proportionally to historical migration flows; and (ii) treatment in state i is exogenous to things happening in state j .

⁶²This is not altogether surprising given that our results are robust when accounting for inventor rather than assignee-based locations.

⁶³Details on the first stage results can be found in the main text.

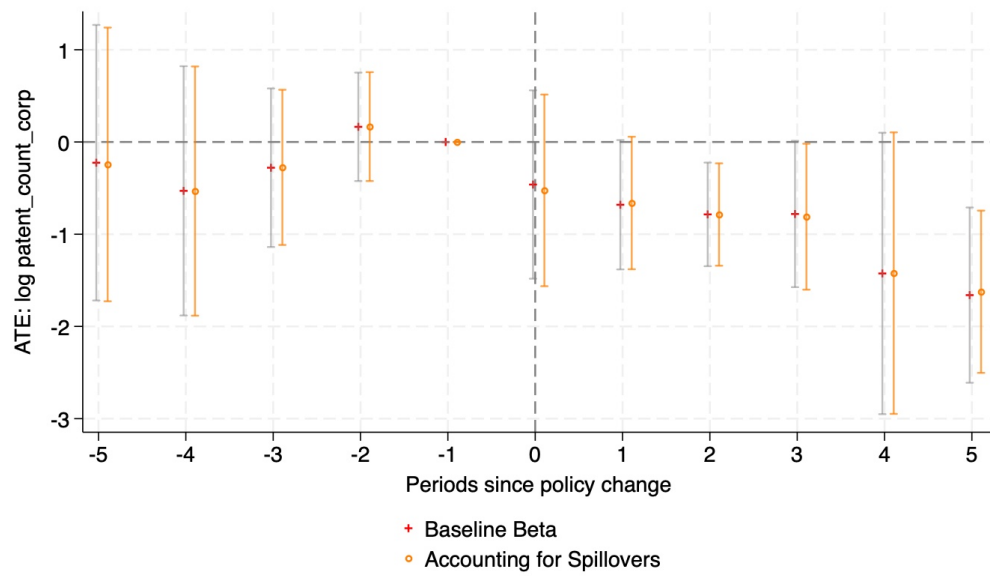
⁶⁴Note that this is consistent with but conservative relative to Johnson et al. (2023a)'s conclusion that economy-wide losses are *larger* than state-level losses.

Figure 15: 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 1, 2, and 3 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a); 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 51.

Figure 16: Updated Estimated Effect of Changes in NCA Enforceability on Log Patent Count

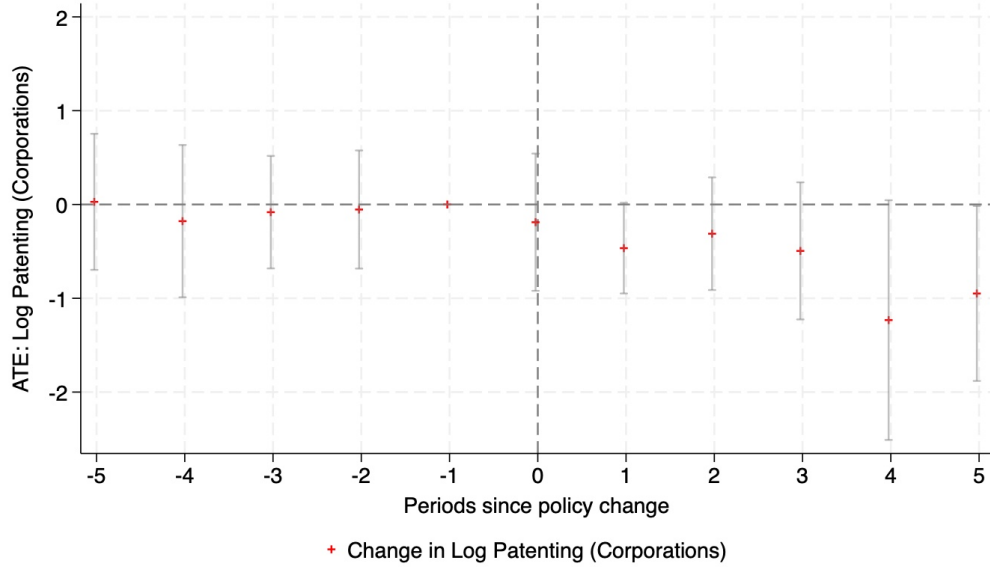


Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log of state-level corporate patenting in year h relative to the time of the policy change ($h = 0$) before accounting for spillovers (in red) and after accounting for spillovers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

D Robustness Checks

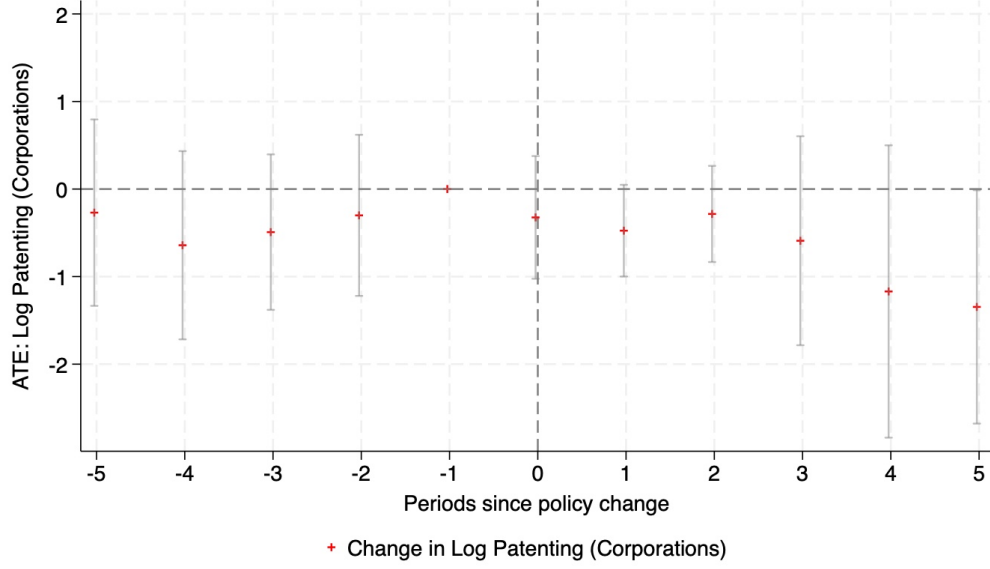
D.1 Alternate Patent Location Definition

Figure 17: 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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 18: 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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.

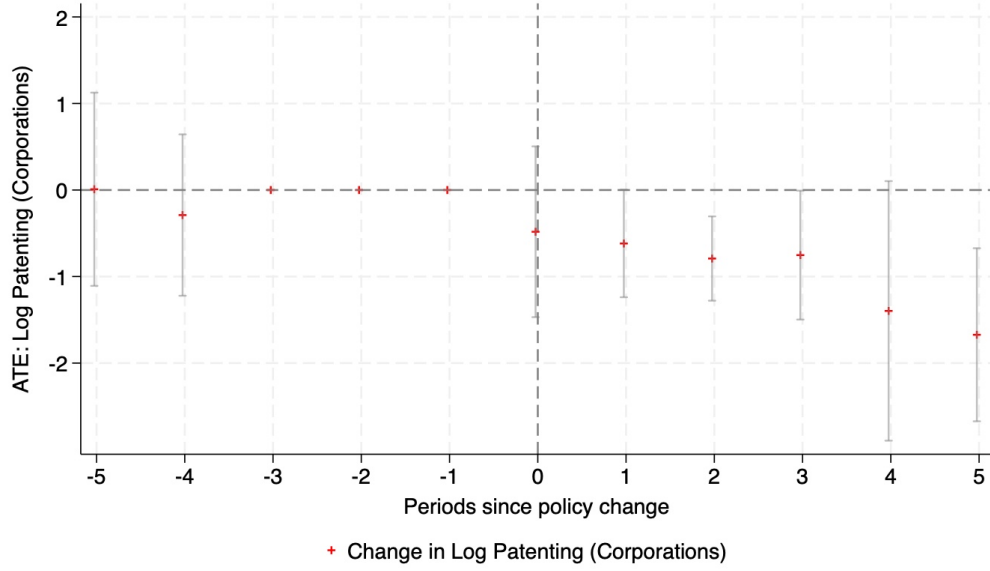
D.2 Example Results with Outcome Lags in LP-DiD

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:

$$\begin{aligned}
 y_{i,t+h} - y_{i,t-1} &= \beta_h \cdot \mathbb{I}_{i,t} \cdot \Delta X_{i,t} && \text{treatment (change in index)} \\
 &+ \sum_{k=1}^K \gamma_k^h \cdot y_{i,t-k} && \text{outcome lags} \\
 &+ \delta_{t+h} - \delta_{t-1} && \text{time effects} \\
 &+ \epsilon_{i,t+h} && \text{for } h = -H, \dots, H,
 \end{aligned} \tag{4}$$

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).

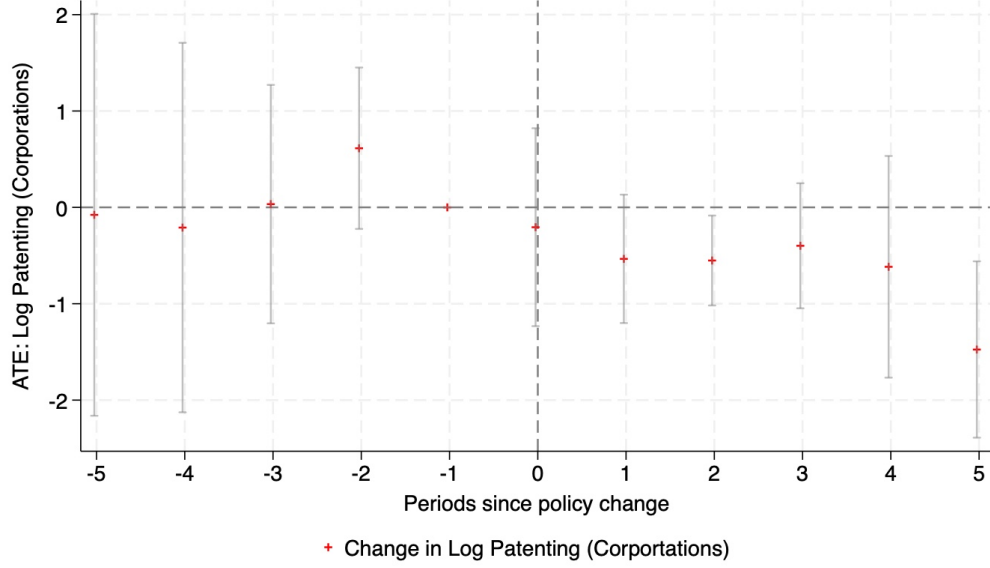
Figure 19: LP-DiD Coefficient Estimates: Log Patent Count - Conditioning on Lagged Outcomes



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 4 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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.

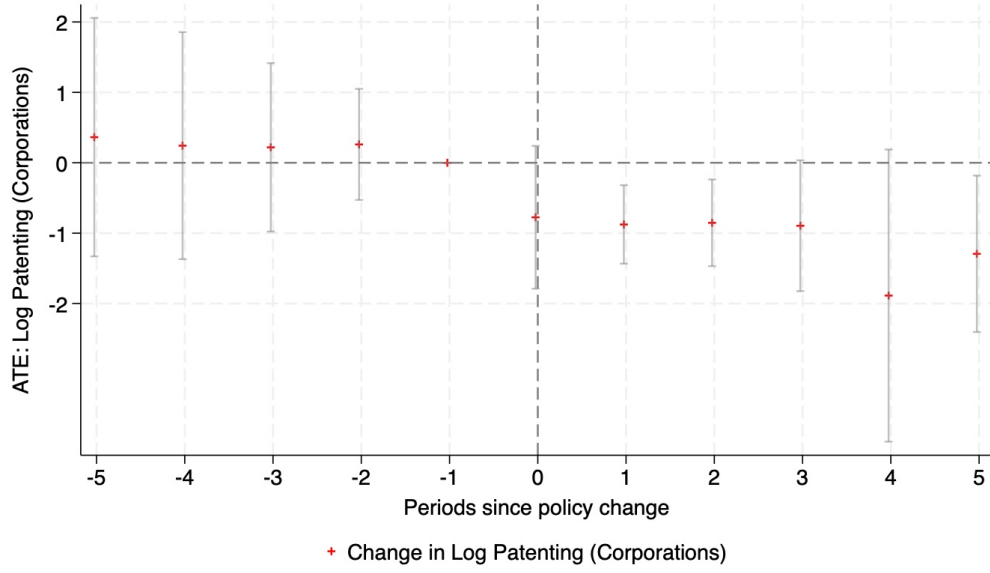
D.3 Example Results with Alternate Weighting

Figure 20: 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: USPTO (2016); Marx (2022), as expanded by 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.

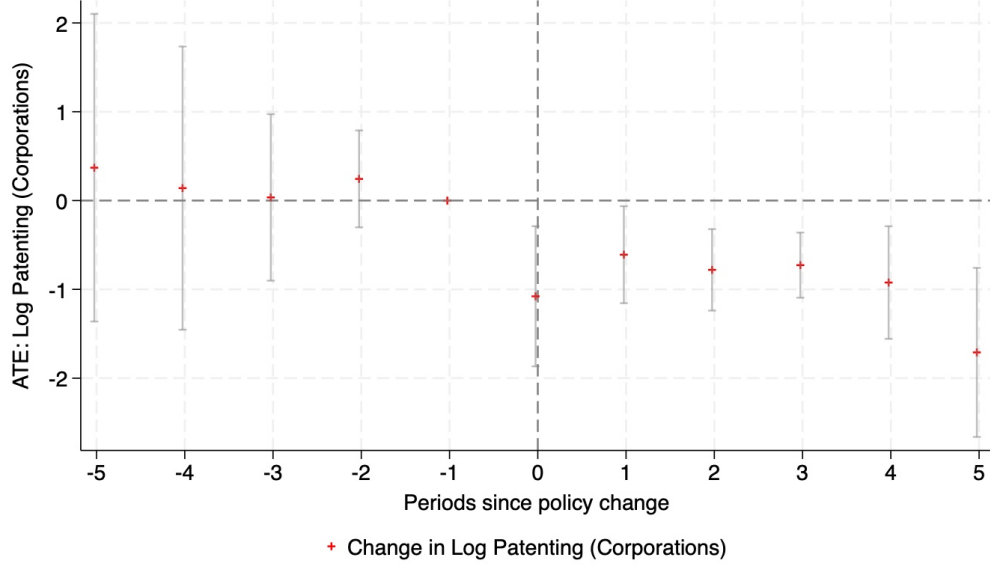
Figure 21: LP-DiD Coefficient Estimates: Log Patent Count - Weighted by Share of Patents



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: USPTO (2016); Marx (2022), as expanded by 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

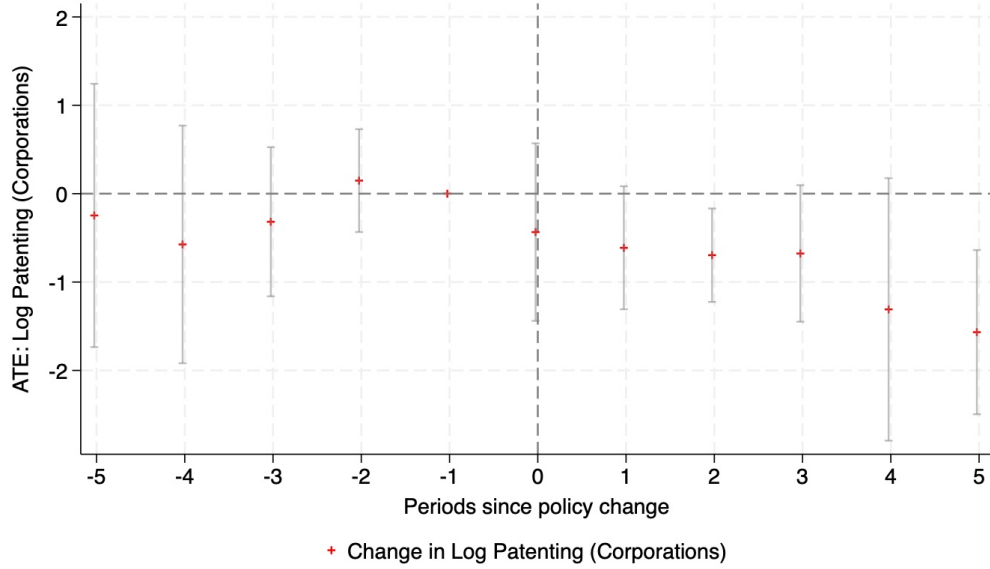
Figure 22: LP-DiD Coefficient Estimates: Balanced Panel



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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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.

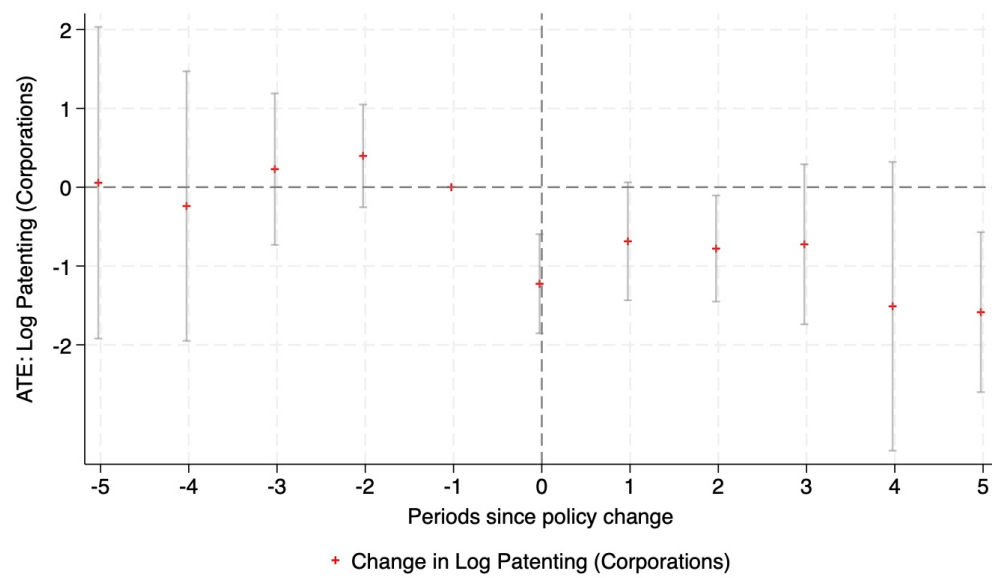
D.5 Alternative Sample Definitions

Figure 23: 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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.

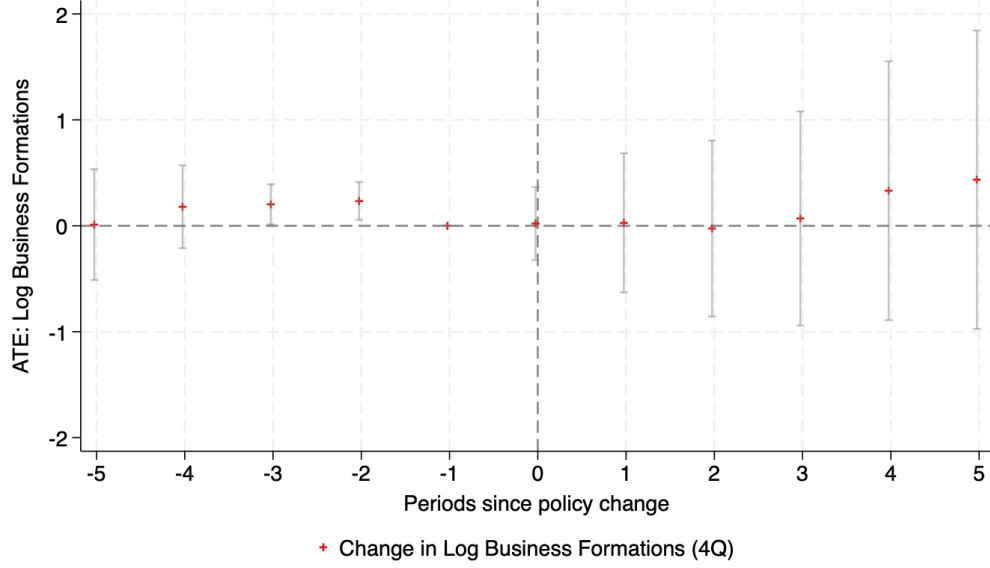
Figure 24: LP-DiD Coefficient Estimates: Log Patent Count - Strengthenings Only



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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). 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.

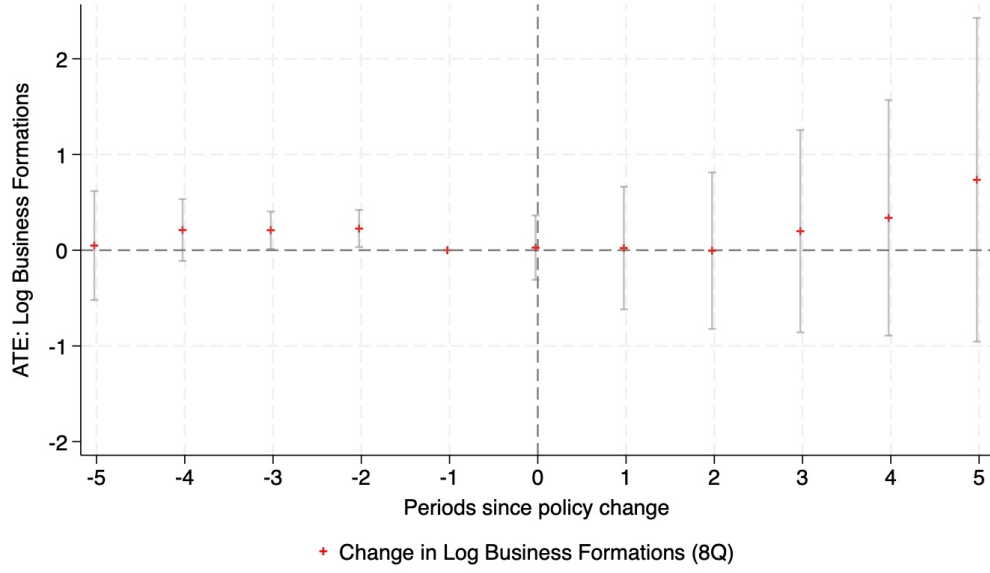
D.6 Entry Robustness Checks

Figure 25: LP-DiD Coefficient Estimates: Log Entry (Four-Quarter Business Formations)



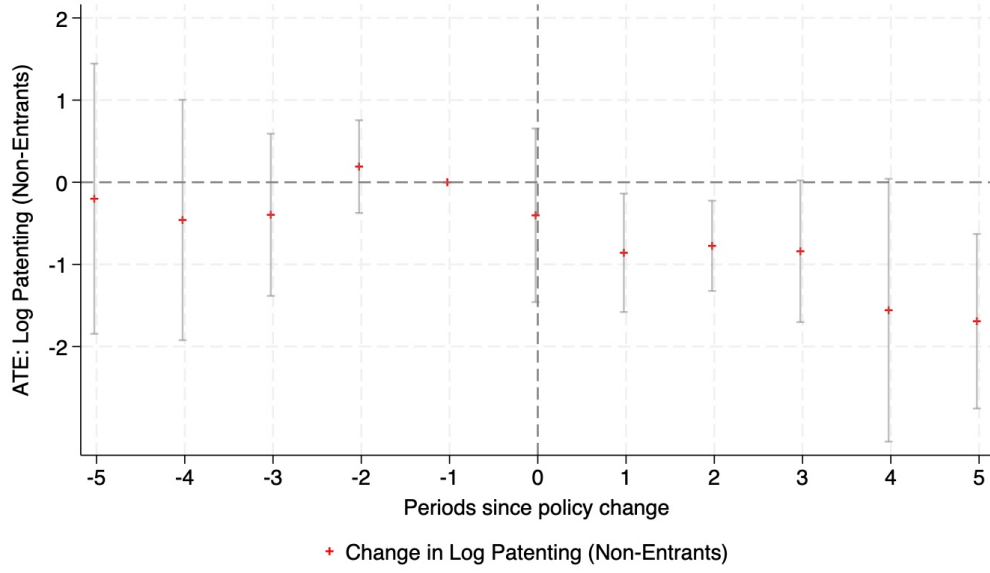
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the log state-level count of business formations within four quarters of the year h relative to the time of the policy change ($h = 0$). Details on the econometric specification 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: US Census Bureau (2022b); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the business formations data are available in Section 2.4. Details on the index are available in Section 2.1 and Appendix Section B.

Figure 26: 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: US Census Bureau (2022b); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the business formations data are available in Section 2.4. Details on the index are available in Section 2.1 and Appendix Section B.

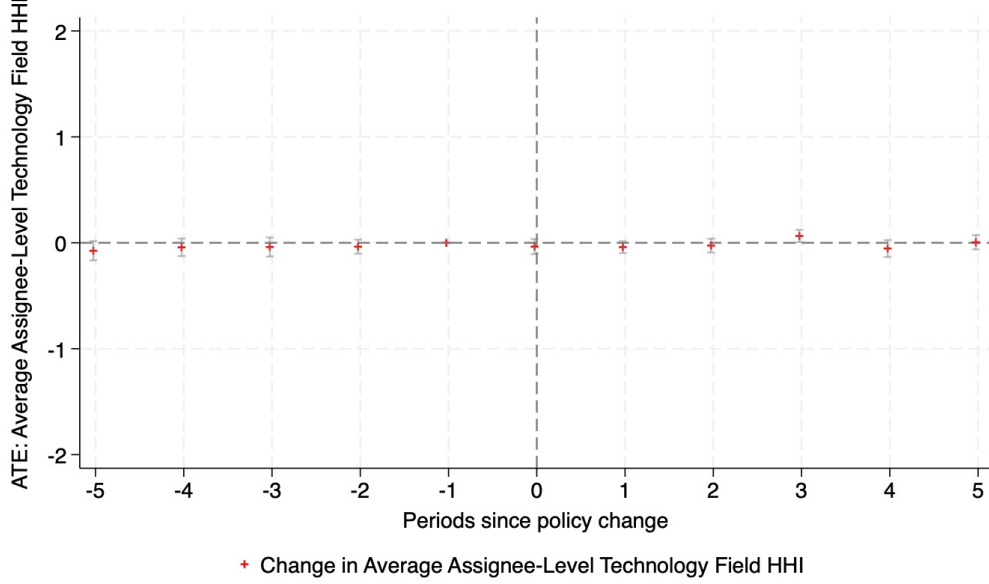
Figure 27: LP-DiD Coefficient Estimates: Log Patent Count – Non-Newly-Founded Firms



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: USPTO (2016); Ewens and Marx (2024); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the index are available in Section 2.1 and Appendix Section B.

D.7 Incumbent Incentive Robustness Checks

Figure 28: LP-DiD Coefficient Estimates: Average Assignee-Level WIPO Technology Field HHI



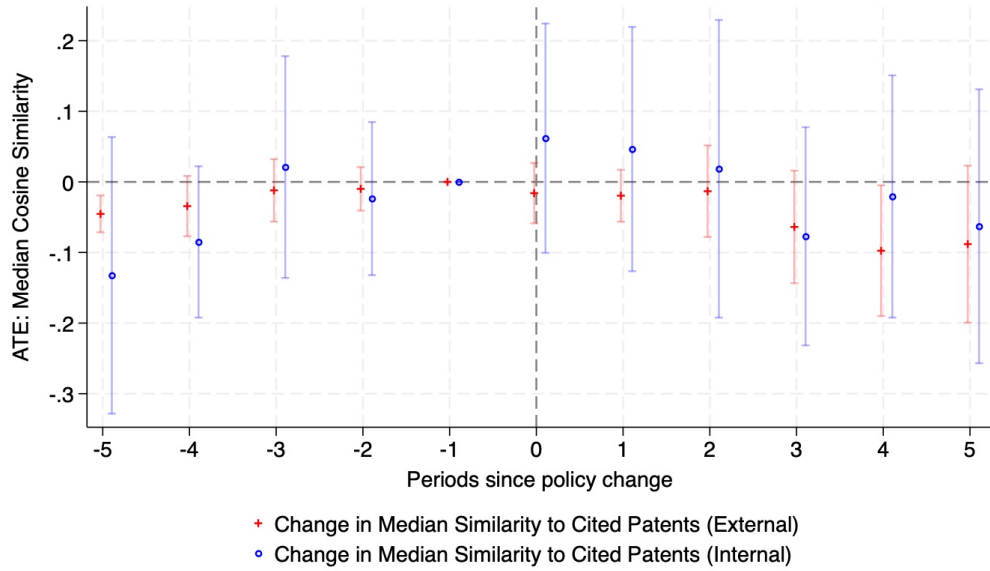
Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the state-level average assignee-level HHI across WIPO technology fields (i.e., the average sum of squared patent shares in a given WIPO technology field by assignee, state, and year). 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the index are available in Section 2.1 and Appendix Section B.

D.8 Labor Mobility and Knowledge Diffusion

To focus even more on the substance of inventions, we also assess the similarity (in cosine distance) to backward cited patents using the Whalen et al. (2020) approach. **Appendix Figure 29** shows the average similarity to cited patents, split by references to inventions within and outside of the firm. Similarity to external citations declines, while similarity to own-firm citations does not.⁶⁵

⁶⁵Although this effect size is not as large as some of our other findings, it is still striking given that one might have expected selection on the now-smaller number of external citations such that similarity would increase.

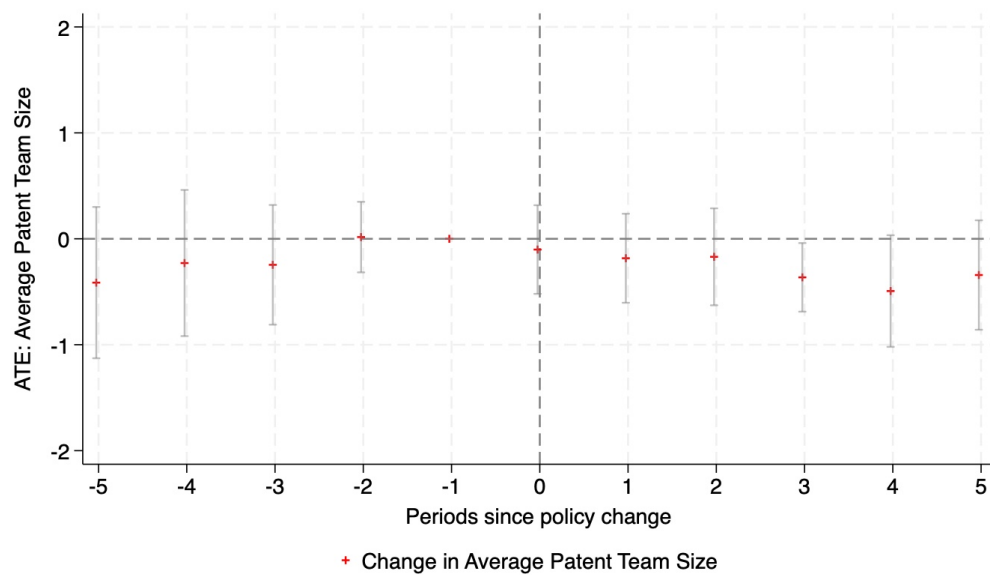
Figure 29: Estimated Effect of Changes in NCA Enforceability on Similarity to Cited Patents



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the median cosine similarity of patents to their backward citations, split by citations to patents assigned to the same firm and those assigned to other, external 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: Whalen et al. (2020); USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a); 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 51.

We find that increased NCA enforceability may cause the size of patent inventor teams to shrink slightly (**Appendix Figure 30**). The effects are not statistically significant in all years and the magnitudes are relatively small, so we do not want to over-index on this result. However, we note that this could be consistent with a setting where recruiting becomes harder and some employees leave the industry entirely to escape their NCAs – i.e., take “career detours” as described in Marx and Fleming (2012) – and/or a setting where lower mobility motivates the firms to rely on smaller teams because they do not need to spread knowledge and research activities across workers as much.

Figure 30: LP-DiD Coefficient Estimates: Average Number of Inventors Per Patent



Plot of the estimated average treatment effect of a 0 to 1 change in NCA enforceability (according to the normalized index) on the state-level average inventor team size. 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: USPTO (2016); Marx (2022), as expanded by this paper, normalized to be $[0,1]$ rather than $[0,600]$; US Census Bureau (2022a). Details on the index are available in Section 2.1 and Appendix Section B.