Non-Compete Agreements and Labor Allocation Across Product Markets

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Abstract

I analyze the effect of non-compete agreements (NCAs) on career trajectories of 600,000 inventors in the US. NCAs limit the choice set of inventors as they are less able to move to competitors. Inventors bypass their NCAs by moving to a new employer in a more distant product market. I identify causal effects using staggered changes in NCA enforceability across US states. Inventors are 25% more likely to move to another industry after higher NCA enforceability. Inventors move to new employers who are less likely to rely on NCAs and patent in unfamiliar technologies. There is a lower quality match between inventors and new employers. Consistent with this evidence, affected inventors are subsequently less productive. Regulation in the form of non-compete agreements put a constraint in the industry choice set of inventors, which leads to some detrimental reallocation of human capital in the economy.

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1. Introduction

Non-compete agreements (NCA) are covenants that restrict employees from working for competitors during and after employment. Employers commonly use NCAs to retain valuable human capital within firm boundaries and to protect trade secrets. There is an ongoing debate in economics, finance, and among policy makers about benefits and drawbacks of these agreements.[1] They can benefit employees, because of increased incentives for employers to invest in employees' human capital. However, the cost is reduced labor mobility (Marx et al. 2009).

I analyze career trajectories of inventors who react to more enforceable NCAs. I add a novel but important dimension to the literature: product markets. An increase in NCA enforcement effectively constrains the within-industry choice set of inventors. Inventors who want to move to a new employer thus face the following trade-off: either 1) terminate the employment contract, wait until the NCA expires to be able to move to a competitor to be able to use industry specific skills or 2) "bypass" the NCA and immediately work for a new employer, however in a more distant product market.

My analysis uses data of around 600,000 US corporate inventors from 1976 to 2018. Patent data provides a suitable laboratory to study NCAs and allocation of labor for several reasons: First, patents provide the precise location of inventors and detailed employment histories. Second, corporate employers of these inventors provide measures of industry affiliation. Third, inventors are highly skilled individuals and, as such, are likely affected by NCAs. Fourth, patent data provides measures for a technology dimension as well as a time series measure of productivity (e.g. citations received and the economic

[1] Among others, see Garmaise (2011); Jeffers (2017); Starr (2019); Marx and Fleming (2012); Samila and Sorenson (2011); He (2021). There are also recent policy proposals related to NCAs e.g. https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/09/fact-sheet-executive-order-on-promoting-competition-in-the-american-economy/

value based on employers' market reactions to patent grants) on a granular level.

Staggered changes of NCA enforceability across U.S. states provide variation for estimating causal effects. In a staggered difference-in-differences panel regression, increases in NCA enforcement are positively related to the probability that an inventor moves to another SIC 4-digit industry. 2 in 100 additional inventors react by moving to another industry per year. This implies a probability increase of 50%. I find similar evidence when using textual analysis based measures of product competition. The baseline regression uses inventor and year fixed effects, and thus exploits the staggered timing of 9 NCA enforcement increases across states either in the form of precedent-setting court cases or state laws. There is no effect for decreases in NCA enforcement.

Econometric theory provides guidance on the event study design: I compare treated inventors (i.e. those exposed to an increase in NCA enforceability) to never-treated in an event time framework (Baker et al. 2022; Borusyak et al. 2021, de Chaisemartin and d'Haultfoeuille 2021, Callaway and Sant'Anna 2021, Sun and Abraham 2021). I match treated inventors to control inventors based on their quality as measured by number of patents and the number of citations received, and to proxy for technological shocks, I also match on patent technology class. NCA-induced industry moves do not increase suddenly, but rather over time. The economic magnitudes of the event study indicate a 25% increase in industry mobility. Consistent with a causal interpretation of the results, there are no pre-trends.

If increases in NCA enforcement cause industry mobility, then inventors that are likely bound by an NCA should drive this result. Unfortunately, individual contracts of inventors remain unobserved. However, I compute a firm level proxy as follows: First, I obtain all annual and quarterly (10-K and 10-Q) reports of the employers in the sample from 1996-2018. These filings often include contract information and NCAs of senior employees. I compute a dummy variable equal to one if a firm relies on NCAs. The assumption is that to some extent, this measure proxies for the presence of NCAs on an inventor level. I estimate a triple-difference regression, and indeed, the effect seems to be present only for inventors whose employers do rely on NCAs. This is in line with a causal interpretation of the results.

I subsequently analyze to what extent NCA-induced industry movers are different compared to other, what I refer to as unconstrained, industry movers. Inventors who move after an increase in the enforcement of NCAs subsequently work for firms that are less likely to rely on NCAs. This is aligned with the interpretation that inventors avoid NCAs in their future employment.

Next, I calculate a measure for matching quality between inventors and their new employers based on patent technologies. The technological similarity between inventor and her new employer is reduced by 20% after an increase in NCA enforcement. Regulatory frictions in the form of NCA enforcement and the associated limited choice set of inventors thus leads to a lower matching quality in the labor market. Also, inventors subsequently patent in, what to them are, unfamiliar technologies.

The natural follow-up question to ask is: What is the effect on productivity for NCA-induced industry movers? On one hand, it might be beneficial to society if increased inter-industry mobility leads to more idea recombination, and thus more innovation. On the other hand, inventors might perform worse after a NCA-induced industry move. NCA-induced industry movers subsequently perform 10%-20% worse as measured by citation weighted or economic value of patents, respectively.

Since NCAs are usually expiring after the termination of the employment contract, an employee faces the following trade-off: Either be able to move immediately after contract termination to a firm which is further away in the product market. Alternatively, terminate the employment contract and wait until the NCA expires to join a close competitor. The evidence confirms the presence of this trade-off, as the duration between two employment spells increases after an increase in NCA enforcement, especially for inventors who move to close industry competitors.

Taken all this evidence together paints a consistent picture: increased NCA enforcement leads inventors to move to new employers in more distant product markets. This is associated with inventors moving to employers which rely less on NCAs. Inventor-firm matches are of lower quality and inventors subsequently patent in unfamiliar technology. The results are consistent with the hypothesis that labor market regulation in the form of increased enforcement of NCAs constrain the labor market choice set of inventors. This leads to detrimental outcomes for reallocated inventors in the economy.

This paper contributes to the literature on real effects of labor market frictions. Previous research has shown that NCAs lead to lower labor mobility (Fallick et al. (2006); Marx et al. (2009); Balasubramanian et al. (2020)), as well as a brain drain of enforcing states (Marx et al. (2015)). I add a product market dimension to this literature. Inter-mobility increases, as inventors respond to NCAs by moving to firms in other industries. The paper is thus closely related to Marx (2011), who provides survey evidence consistent with the empirical results presented in this paper. My setting allows to analyze long run employment outcomes and an important outcome for society: productivity of labor, in this context innovation output.

I also add to the allocation of labor literature (Babina et al. (2020); Babina (2020); Hombert and Matray (2017); Hombert and Matray (2018)). I show how labor market frictions can lead to some reallocation of labor in the economy, which is likely an unintended consequence for policy makers in the context of NCA enforcement. Lastly I add to the literature on firm and industry boundaries and the productivity of labor (Seru (2014); Hacamo and Kleiner (2022)). While unconstrained inter-industry mobility seems to be beneficial for society, NCA-induced industry mobility is detrimental.

2. Data

2.1. Employment Histories of Corporate Inventors

I obtain data on corporate innovation from 1976 until 2020 from two sources. I obtain patents matched to firms from Kogan et al. (2017), commonly referred to as KPSS. This list is complemented with the DISCERN database of Arora et al. (2021).[2] The first dataset is thus a list of patent numbers and an associated unique corporate identifier. The next step is to match individual inventors to these patents. The United States Patent and Trademark Office (USPTO) provides detailed data on patents such as who invented which patents, the location of the inventor, and the application year which is used to proxy for innovation generation. Most importantly, the USPTO provides disambiguated inventor-level data.[3] Disambiguated data allows researchers to track individual inventors over time. I obtain this data from patentsview.org.

2.2. Non-Compete Agreements: Institutional Details and Data on Enforcement Changes

What exactly are Non-Compete Agreements? A NCA usually puts limitations on industry, geographic reach (which ranges from a well defined radius, a state, country or even worldwide), and duration (mostly 1-2 years) of an employee. The Appendix lists some examples of NCAs. Microvision states in the annual statement that the firm heavily relies on NCAs. Nuance Communications explicitly mentions that they prohibit employees "from working for an employer who is engaged in activities or offers products that are competitive with the activities and products of the company."

[2] The KPSS data with matched patent data is updated until the end of 2020 and available here: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data; The DISCERN database includes patents matched to firms (including subsidiaries) until 2015 and is available here: https://zenodo.org/record/4320782

[3] The provided data builds on previous efforts such as the NBER patent citation data file as well as disambiguated inventor-level data of Li et al. (2014).

I summarize changes in state-level NCA enforcement in Table 1. I rely on Ewens and Marx (2018), who provide an extensive discussion on court rulings and legislative changes from 1985-2016.[4] Kini et al. (2021) is the second source of data. They extend a score of NCA enforceability across states originally developed by Garmaise (2011) to the years 1992-2014.

What happens when NCAs are more enforceable? Restrictions included in a NCA and what is ultimately enforceable can differ strongly. States such as California are famously opposed to enforcing NCAs. Florida is on the other end of the spectrum and enforces NCAs most strictly. Often, NCAs are enforceable conditional on passing a "reasonableness" test. After a 1996 legislative change, NCAs in Florida need to protect "legitimate business interests" in order to be enforceable. This clarified previous uncertainty and shifted power towards employers.[5]

For some specifications, I use data on firm-level reliance on NCAs. I proceed in similar fashion as Kini et al. (2021). First, I obtain form 10-K and form 10-Q filings from EDGAR. I parse and strip the text of figures, pictures and html tags. I obtain identifiers from historical Compustat from WRDS servers, as well as a historical CIK-CUSIP mapping.[6] Form 10-K and form 10-Q filings commonly include NCAs of senior employees at a firm. I use the information to construct a panel of US corporations with an indicator variable equal to 1 if the corporate employer mentions the use of a NCA either in an executive/board contract or mentions the reliance on NCAs in the annual statement. I do

[4]The data is available here: https://github.com/michaelewens/Non-compete-Law-Changes

[5]There are many other examples on how NCAs become more enforceable. For example, the Ohio Supreme Court decided in 2004 that a sufficient consideration to uphold a NCA was continued employment. Another example is Idaho, which changed to a so-called "blue pencil" rule where a judge can modify the contract to make it more reasonable whereas in other states one invalid part of a NCA renders the whole agreement void. Interested readers should refer to Marx and Fleming (2012) for history and background literature. Ewens and Marx (2018) provide extensive details on individual court cases and legislative changes

[6]Ekaterina Volkova provides this mapping here: https://sites.google.com/view/evolkova/data-cik-cusip-link

this similar to Acikalin et al. (2022) and screen for instances of "non-compete agreement", "covenant not to compete", etc. I compute a panel on a firm-year level and construct a dummy variable equal to one if a firm relies on NCAs. This panel is comprehensive from the year 1996 onwards, so specifications using this information range from 1996-2018. In my sample, 54% of firms rely NCAs. This is close to previous survey and empirical evidence. To compare, Starr et al. (2021) find that almost one fifth of all employees in the US are bound by NCAs. The share of NCAs for technical workers is around 50% (Marx 2011), 62.5% for CEOs with employment contracts (Kini et al. 2021), and 70% for corporate executives (Garmaise 2011).

2.3. Sample Construction and Descriptive Statistics

The sample construction starts with all corporate innovation from the two sources mentioned previously. This gives a mapping with a unique identifier for each corporation and the patent number assigned by the USPTO. In principle, data on corporate patents is available from 1926, however the USPTO provides digitized patent information with disambiguated inventor data from 1976 onwards, which marks the start of the sample. In a next step, I merge the inventors of all corporate-owned patents with the disambiguated inventor data. The resulting dataset is a panel at the inventor-year level.

I identify industry employment changes as follows: The inventor files two subsequent patent applications for a different employer with a different industry affiliation. I follow the previous literature (Song et al. 2003; Marx et al. 2015) and use the yearly midpoint between two subsequent patents to proxy for the year of employment change.[7] The ap-

[7]Patent-based measures of employment histories thus include measurement error. On average, there is a gap of 0.9 years between two subsequent patents filed by the same inventor. The median number of years between two filings is zero. When alternatively limiting the sample to patent filings with at most one year between two subsequent patents, the results become stronger.

plication year rather than the grant year is used, in order to have a more timely measure of innovation creation[8] and employment changes. I remove inventors from the sample who only patent once in the sample period. All regressions include inventor fixed-effects, so these inventors would not provide any meaningful variation on labor market employment.

Innovation is an ideal laboratory for several reasons: First, the universe of corporate patenting in the last 40 years provides tractable employment histories of inventors based on granted patents.[9] In the context of this paper, it also seems plausible that highly skilled human capital such as inventors, are likely to be affected by NCAs.

Second, patent documents also capture the location (on a city level) of each inventor listed on a patent. This greatly improves measurement for empirical research that uses location-based variation in treatment. Previous studies often proxy for location using the headquarter location of the employer.

Third, corporate innovation data allows to look at two distinct but related dimensions: measures of product and technology similarity. Product markets for employers are readily available as SIC and NAICS industry codes, as well as text-based industry classifications following Hoberg and Phillips (2010) and Hoberg and Phillips (2016). The latter is a measure with desirable econometric properties which can be used to measure the similarity between the old and the new employers of inventors. Patent data provides technology classifications of every patent (e.g. CPC, WIPO, IPC). This is useful as it allows researchers to compute technology similarities between the patents of inventors and their employers.

Fourth, and lastly, patent data provides a useful metric on a patent basis to measure

[8]This avoids a lag between applying for and being granted a patent, which is 4 years at the median.

[9]The caveat here is that non-patented innovation is unobserved and thus overall labor mobility is likely underestimated

the productivity of an inventor over time. A researcher can thus observe the number of patents, the number of citations received[10] Lerner and Seru (2021), and the economic value of patents (Kogan et al. 2017). The latter measure is available for all patents granted until 2020 and is comprised of a USD value on a patent basis. The measure is calculated using stock market reactions of listed patent assignees on the grant day of a patent. This measure is available before and after an employment change.

Table 2 shows descriptive statistics. The timeframe is from 1976-2018. In total, the panel includes 5,183,982 inventor-year observations. This includes data of around 1.8 million patents of roughly 0.6 million inventors. The sample includes 6,345 listed firms as employers. An industry move is defined as a move between two firms which have different SIC 4-digit industry codes. This appears in 4% of all inventor-year observations. I compare this to the previous numbers in the literature such as Melero et al. (2017) who show based an patent application data, that inventors move employers (without considering industries) at a rate of 10% per year. The mean number of patents granted is 5.5 and the number of truncation adjusted citation-weighted patents is 9.8.

3. Staggered State-Level Changes in Non-Compete Enforcement

3.1. Baseline: Non-Compete Agreements and Industry Mobility

Using staggered changes in NCA enforcement across US states, I estimate the following panel regression:

$$IndustryChange_{i,s,t+1} = \beta \times NCA_s \times Post_{s,t} + \theta_i + \phi_t + \epsilon_{i,t} \tag{1}$$

[10]Newer patents mechanically have less time to accumulate citations than older patents. In order to mitigate this problem I follow Hall et al. (2005), Dass et al. (2017), and Lerner and Seru (2021). When using citations as a measure of innovation output, I adjust all cumulative citations received until June 2022 and perform a truncation adjustment by adjusting with respect to year and technology class.

where i represent inventor i, located in state s, in year t. The dependent variable $IndustryChange_{i,s,t+1}$ is defined as equal to one if an inventor moves between two firms with different 4-digit SIC industry codes.[11] I separate the treatment indicator into $NCAIncrease{\times}Post$ and $NCADecrease{\times}Post$ whether state s decreased, or increased the enforceability of NCAs. Panels A and B of Table 1 provide an overview of these events. The variables θ and ϕ are inventor and year fixed-effects, respectively. Year fixed-effects account for year-specific shocks to mobility. Inventor fixed-effects control for time-invariant unobserved factors on the inventor level. I cluster standard errors on a state level, which is the level of treatment. Different levels of clustering do not change the results. Essentially, the methodology estimates a difference-in-differences regression, which compares inventors located in states with a change in the enforcement of NCAs with those who did not.

Table 3 shows the results. An increase in NCA enforcement leads to an increase in industry mobility of 2%. Thus, an increase in NCA enforcement leads 2 out of 100 additional inventors to change SIC 4-digit industries annually. Given that the average industry mobility in the sample is 4% per year, this implies a 50% increased probability that an inventor moves to another SIC 4-digit industry. Panel B shows that there is no effect for decreases in NCA enforceability.

This analysis is based on staggered difference-in-differences across 15 states, 9 of which experienced an increase and 6 a decrease during the sample period. A necessary condition for a causal interpretation is that treated and untreated inventors share parallel trends. To visually present pre-trends, as well as incorporate recent developments in the econometrics literature, the following section explicitly looks at the timing of the treatment effect and dynamic effects.

[11] Alternatively, I use SIC 3-digit, NAICS 6 and 5-digit, as well as a textual product market similarity measure in a different specification.

3.2. Event Study and Dynamic Effects

I estimate the following event study regression:

$$IndustryChange_{i,s,t+1} = \sum_{k=-5}^{k=+10} \delta_k \times D_k + \sum_{k=-5}^{k=+10} \beta_k \times D_k \times NCAIncrease_{s,t} + \theta_i + \phi_t + \epsilon_{i,s,t} \quad (2)$$

where D_k are time dummies relative to the NCA enforcement increase. The coefficients of interest are β_k which capture the treatment indicator interacted with 4 pre-treatment dummies and 10 post-treatment dummies. All coefficients are estimated relative to one year before treatment.

I use nearest neighbor matching to compare treated and control inventors. I match inventors based on year of activity (whether they are currently employed at a firm), lagged number of patents, and lagged total citations. I use these two variables to match inventors of a similar quality. I also include patent technology to guarantee that treatment and control inventors are exposed to similar technological shocks. I match the three nearest neighbors with replacement using the Mahalanobis distance. The analysis again includes inventor as well as year fixed effects. I cluster standard errors on the inventor and year level.

A two-way fixed effect estimation of a staggered difference-in-differences design are weighted averages of all possible two-group difference-in-differences estimators (Goodman-Bacon 2021). A potential problem are dynamic treatment effects when we compare early-treated to late-treated inventors (Baker et al. 2022). I follow recent econometric theory when exploiting state-level changes of Table 1. I compare treated with never-treated inventors. Thus, I compare inventors based in states that experienced increased enforcement of NCAs with clean controls: those inventors that did not experience any changes during the sample period. I use a number of recently proposed estimators such as Borusyak et al.

(2021), de Chaisemartin and d'Haultfoeuille (2021), Callaway and Sant'Anna (2021), and Sun and Abraham (2021).

Figure 1 visualizes the results from Equation 2. They are well-aligned with the baseline evidence. There is no sudden jump in the probability that an inventor changes industries, but rather a steady increase over time that is statistically significant starting from year 2 after the treatment. In year 3, the effect is around 0.01, which is a 25% increase in the probability that an inventor moves across industries. The alternative estimators are close to the OLS estimates. Figure A3 shows that there is no effect when looking at decreased NCA enforcement.

3.3. Is the Effect Stronger in the Presence of Non-Compete Agreements?

If NCA enforcement increases indeed lead to increased inter-industry mobility of inventors, then we would expect this effect to be stronger for inventors that are in fact bound to a NCA. Unfortunately individual level NCAs of inventors are unobserved. However, employers might differ on how much they rely on NCAs. I therefore compute a proxy on a firm level as follows: First, I obtain all annual and quarterly (10-K and 10-Q) reports of the employers in the sample from 1996-2018. These filings often include contract information and NCAs of senior employees. I compute a dummy equal to one if a firm relies on NCAs. The assumption is that to some extent, this firm-level dummy is a proxy for the presence of NCAs on an inventor level.

I formally test whether increased enforcement of NCAs leads to more industry mobility especially for those inventors employed at firms that use NCAs. For this purpose, I run a triple difference-in-differences regression as follows:

$$IndustryChange_{i,s,j,t+1} = \beta \times NCAIncrease_{s,t} \times Post_{s,t} + \\ \delta \times NCAIncrease_{s,t} \times Post_{s,t} \times EmployerNCA_{j,t} + \theta_i + \phi_t + \epsilon_{i,s,j,t} \tag{3}$$

where $EmployerNCA$ is an indicator variable equal to one if the employer heavily relies on NCAs. The parameter of interest is the triple interaction term $NCAIncrease \times Post \times EmployerNCA$. The variable is equal to one only for inventors in years after an increase in NCA enforcement, and additionally employed at firms who rely on NCAs.

Table 4 shows the results. The interaction coefficient $NCAIncrease \times Post$ is now either insignificant or for SIC industry definitions negative and significant. This interaction coefficient can be interpreted as the treatment effect for inventors who do not work for NCA relying employers. The triple difference-in-differences term is positive and significant throughout. In economic terms, inventors in years following treatment and employed by NCA-relying firms experience an increase in industry mobility of 2%. The observed effect seems to be confined to inventors that are likely bound by NCAs. Subject to the constraint that the proxy for NCA on an employer level is imperfect, this is aligned with a causal interpretation of the results.

3.4. Non-Compete Agreements and Product Market Similarity

The previous analyses rely on standard, fixed industry classifications such as SIC codes. In the following, I analyze whether the results generalize to a continuous version of industry similarity between two firms. I will rely on the textual based industry scores of Hoberg and Phillips (2016). This provides several improvements, such as 1) the industry definitions are not fixed over time and a continuous measure can vary between two identical firms across years, 2) the measure captures product market proximity irregardless of whether two firms are in the same industry or not. Standard classifications can only provide a 0 or 1, which means either two firms are in the same industry or they are not. The regression analyzes the question: Are inventors moving to employers which are further away from their old employers after an increase in NCA enforcement? Formally, I run the following regression:

$$y_{i,t} = \beta \times NCAIncrease_{i,t} + \phi_t + \epsilon_{i,t} \tag{4}$$

where $y_{i,t}$ is the product market similarity between the previous and the new employer obtained from Hoberg and Phillips (2016). $NCAIncrease$ is a dummy variable equal to one if the inventor is exposed to an increase in NCA enforcement. The sample is thus composed of all inventor mobility events. An inventors move is included in this regression as long as the inventor is based in the US and moves between two publicly listed firms with available data.

The results are shown in Table 5. Indeed, inventors exposed to increased NCA enforcement move to firm that are on average around -2% less similar in product market similarity. To put this into context, within the universe of all inventors mobility events, the average product market similarity is equal to 6.8%. An increase in NCA enforcement thus leads to inventors moving to a firm that is 22% less similar in the product market compared to other inventor mobility events.

3.5. Does Increased Non-Compete Enforcement Cause *Industry Mobility?*

In order to interpret the results as causal, the critical assumption is that treatment and control inventors are equally likely to change industries in the absence of treatment. As a necessary but not sufficient condition, I can visually assess whether treated and control inventors experience parallel pre-trends. Reassuringly, the event study in Figure 1 shows that this is the case.

The delayed effects raise the question whether non-compete enforcement increases *should* lead to immediate labor market effects. There are several reasons why we should not expect an immediate response: For example, the Florida law change in 1996 was explicitly only applicable to contracts signed after July 1, 1996.[12] This would mean that only employees that start working after this date are exposed to increased NCA enforcement. To increase the chances of legal protection, Ewens and Marx (2018) note that employers commonly require their employees to sign updated employment contracts, which might not lead to immediate responses. This is supported (for the Georgia 2010 case) by Ewens and Marx (2018) who interviewed an employment attorney, who stated: "when the new law went into effect (including our firm), many employers revised their employment and restrictive covenant agreements to take advantage of the law". This practice would not lead to an immediate reaction. Setting the legal point of view aside, there are additional considerations for a delayed response from the point of view of employees. Inventors willing to move might not be well aware of the details of their NCA. They might learn about the increased enforcement of NCAs years after. An employee is prohibited from joining a close competitor 1-2 years *after* the termination of the contract. Assuming that the desire to work for a new employer is uniformly distributed across inventors, an inventor who wishes to move faces the following trade-off: terminate the contract and wait until the NCA expires or alternatively join a firm in a different industry. Thus, there is no reason we should expect sudden effects, but rather an increase over time which leads to a new equilibrium in the labor market.

A potential problem for a causal interpretation is whether state legislative changes are correlated with other factors that determine industry mobility. State legislative changes

[12]However Ewens and Marx (2018) note that continued employment suffices as consideration.

might be problematic if the desired policy change is anticipated. There are two reasons why this is unlikely to be a threat to identification in my setting. First, Jeffers (2017) shows that the state-level shocks are unrelated to macroeconomic conditions and cannot be easily predicted. Given the focus on inter-industry mobility, the positive effect on industry changes of inventors is a plausible unintended consequence of regulatory changes. Nevertheless, the analysis is repeated and is robust when only considering court cases, which are arguably more exogenous compared to state legislative changes.

Overall, the findings are consistent with interview evidence of Marx (2011), where employees admit to taking career detours given that their NCA prohibited them from working in similar industries for the next 1-2 years. Marx (2011) interviewed one speech recognition professional who left the industry after being fired by his co-founder. "Well, if I'm ever gonna leave, what would I do for 2 years if I couldn't do speech recognition?"

4. Channels

The following section will analyze how NCA-induced industry mobility differs from unconstrained (absent any NCA enforceability changes) industry mobility. I define NCA-induced as those inventors who move after an increase in NCA enforcement. Unconstrained industry mobility are industry mobility events of inventors in states that did not see increases in NCA enforcement. The following subsections will look at several dimensions: 1) how new employers differ from old employers, 2) how new employer-inventor matching characteristics differ, and 3) how inventors themselves react in terms of patenting and employment choices.

4.1. Inventors move to Employers who rely less on NCAs

If inventors indeed experience NCA-induced industry mobility, are they more likely to move to firms that do not rely on NCAs? To answer this question, I again estimate equation 4. $y_{i,t}$ is equal to one if inventor i in year t moves to a firm which heavily relies on NCAs. As before, this is a dummy variable equal to one if a firm references such contracts either in firm balance sheet statements (10-Ks) or employment contracts obtained from 10-Q filings. The variable $NCAIncrease$ is equal to one if the inventor is located in a state which experiences an increase in NCA enforceability. The sample is composed of all inventors who move across firms, so this specification allows to compare differences in the type of employer inventors move to using the shock as a treatment indicator.

The results are shown in Panel A of Table 6. An inventor exposed to increased NCA enforcement moves to a firm that is around 5% less likely to be NCA intensive. Across all inventor mobility events, the mean value is equal to 47%. The effect thus indicates a 10% decrease in firm-level NCA intensity. Inventors seem to move to firms that are less likely to rely on NCAs. This result is consistent with the interpretation that to some extent, the mobility events might be NCA-induced.

4.2. NCA Enforcement leads to Worse Inventor-Firm Matching Quality

In the following specification, I analyze whether inventors who experience an increase in NCA enforceability move to firms that are less similar to them not just on the product market, but also in a technology dimension. Patent data provides detailed data on technology subsections on the level of inventor as well as the new employer. Specifically, I calculate the following measure on technological similarity between inventor and employer:

$$techsimilarity(i, f) = \frac{if^T}{||i||||f||} \tag{5}$$

I define two vectors that include the distribution of previous patents across 130 technology subsections. I use the subsection of the Cooperative Patent Classification (CPC) scheme for this purpose, which includes 130 different technology subsections. I use all patents of the inventor up until the year before the industry move and all patents in the previous 5 years of the new employer. The technological similarity is equal to a cosine similarity of the two technology distribution vectors. The measure is bound between zero and one, so it takes a value of zero if no patent section aligns between the employer and the inventor. It is equal to one is the distribution of the two vectors across technology subsections is identical. Technological similarity here is used as a proxy for matching quality between inventor and the firm. If the patent technology subsections of the firm and the patents of the inventors are similar, I assume it is a good match. I then estimate equation 4, where y is defined as the technological similarity between inventor i and firm f.

Results are shown in Panel B of Table 6. The patent technology cosine similarity is reduced by 0.08 for after an increase in NCA enforceability. Given the mean value of 0.4 of technology similarity, this is a reduction of around 20%. This highlights that the matching quality between inventors and employers seems to be much lower in the presence of increased NCA enforcement.

4.3. NCA Enforcement leads to Patenting in Unfamiliar Technological Subsections

In the following, I look at whether inventors patent in technologies that are new to themselves. The specification is similar to the previous, however in an event time framework. Formally:

$$y_{i,t} = \sum_{k=-5}^{k=+10} \delta_k \times D_k + \sum_{k=-5}^{k=+10} \beta_k \times D_k \times NCAIncrease_{i,t} + \theta_i + \phi_t + \epsilon_{i,t} \tag{6}$$

where $y_{i,t}$ is a dummy variable equal to one if the inventor is granted a patent in a new technology class in which she did not previously own a patent. Each additional patent is compared to all previous patents by the inventor. If the patent includes a technology class that is new, the dummy variable will be set to one, and zero otherwise. The treatment indicator is set to one if the inventor is moving to another firm in another industry after an increase in NCA enforcement. Control inventors are those who move to another firm in another industry, however disregarding any changes in NCA enforcement.

The results are presented in Figure 2. After a constrained industry move, inventors are more likely to patent in unfamiliar technology subsections. The probability of patenting in unfamiliar technology is increased by more than 5% in the years following industry move.

4.4. Non-compete Agreement Enforcement leads to Longer Employment Gaps

NCAs usually have a period of 1-2 years after the end of the employment contract during which employees are not allowed to move to a close competitor. An inventor who wishes to work for another firm faces the following trade-off: Wait until the NCA expires or move to a firm that is further away in the product market. I try to model this trade-off in a regression and hypothesize the following: When NCAs become more enforceable, inventors wait some additional time until they can more easily join a close competitor. This effect should especially be present for within industry moves as they are most likely to be affected by NCAs. I use the following specification:

$$
\begin{aligned}
EmploymentGap_{i,t} = \beta{\times}NCAIncrease_i, t{+}\delta{\times}Within_i, t{+} \\
\gamma{\times}NCAIncrease_i, t{\times}Within_i, t{+}\theta_i{+}\epsilon_{i,t}
\end{aligned}
\tag{7}
$$

where *NCAIncrease* is a dummy variable equal to one if the industry move is after an increase in NCA enforcement. *Within* is a dummy variable equal to one if the inventor moves to a firm that is in the same SIC 4-digit industry. *EmploymentGap* is the distance in years when an inventor moved between two firms. This is observed in the data by looking at two subsequent patent filing years to different firms by an inventor.

The results are presented in Table 7. Being constrained by increased NCA enforcement seems to have a general positive impact on employment gaps. This is consistent with the general purpose of NCAs. Moving within the same industry seems to be associated with a reduction of the gap by a little less than one year on average. Most importantly, and consistent with the hypothesis, the interaction of NCA enforcement increase and within industry move is positive and significant. An increase in NCA enforceability especially leads to longer employment gaps for those inventors who move to close industry peers.

5. Industry Mobility and Productivity

5.1. NCA-Induced Industry Moves lead to Lower Productivity

What are the effects on productivity if inventors are moving industries in response to NCA enforcement increases? On one hand, it might be beneficial to society if increased inter-industry mobility leads to more idea recombination, and thus higher or more high quality innovation output. On the other hand, inventors might perform worse after a NCA-induced industry move. I introduce a new regression, designed to capture productivity changes after employment changes on the level of individual inventors:

$$Productivity_{i,t} = \beta_i \times Post_i, t + \theta_i + \epsilon_{i,t} \quad (8)$$

where $Productivity_{i,t}$ measures the yearly productivity of inventors based on the economic value of patents or citation-weighted patents. The innovation output is firm specific, which means that all patents of the old employer and all patents of the new employer are included in the regression. The dummy variable $Post$ is equal to one for years after the inventor has moved to another employer. I estimate the regression for each inventor mobility event, i.e. I run all regressions separately. The coefficient β_i thus captures the extent to which the inventor is more or less productive after moving to another employer. This specification has several desirable properties. First, the inclusion of inventor fixed effects removes the non time-varying quality of the inventor. The specification thus uses patent output of the inventor before and after the move to better tease out productivity differences. Second, the specification is not prone to outliers as each inventor mobility event receives equal weight. Third, the coefficient can be interpreted in an intuitive fashion: How much more/less productive is the inventor after the employment change?

I then use the beta coefficients from these regressions in equation 4. The treatment indicator is $NCAIncrease$. It is equal to one for NCA-induces industry changes. It is a dummy variable equal to one if the inventor moves to a firm in another SIC 4-digit industry after an increase in NCA enforceability. The results are shown in Table 8. The productivity after an NCA-induced industry move decreases by 20% for economic value of patents and by 10% for citation-weighted patents. Both productivity measures are statistically significant. Thus, inventors who move in response to increased NCA enforcement subsequently perform worse. This result is consistent with some previous evidence, such as unfamiliar technology, as well as lower matching quality between inventor and new employer.

The constant is positive for both regressions. It seems that on average, moving to another industry seems to be beneficial for inventor productivity.

5.2. Product and Technology Similarity and Productivity

The evidence so far indicates that overall, mobility events seem to be beneficial for the productivity of inventors. However, when inventors are choice constrained the future productivity is lower. To generalize this finding, I look at the performance of all inventor mobility events in the U.S. depending on the distance between the old and new employer in the product and technology dimension. I use the following regression:

$$ProductivityCoefficient_{i,f} = \beta_k \times Product_i, f + \delta_k \times Technology_i, f + \theta_i + \epsilon_{i,f} \qquad (9)$$

where $ProductivityCoefficient_{i,f}$ is defined as the beta coefficient from the inventor productivity regression. It captures to what extent the inventor performs better or worse after moving to another employer. The two variables of interest are product market similarity obtained from Hoberg and Phillips (2016) and the technology similarity calculated from patenting data. I use the last 5 years of patents of the new and the old employer and calculate a cosine similarity based on technology subsections.

The results are shown in Table 9. Both product market as well as technology similarity are positively correlated with future productivity. This is well aligned with the previous evidence. NCA enforcement can be seen as a constraint primarily on the product market dimension. NCA contract limit employees to freely move to close industry peers. The previous evidence also showed that NCA-induced employment changes are also associated with lower matching quality. Both of these effects are likely to have negative consequences for future productivity.

6. Conclusion

Inventors evade their NCAs by moving to new employers in more distant product markets. NCA enforcement increases have a positive causal effect on the probability that an inventor moves across industries. The effect is only present for inventors working for employers which rely on NCA contracts. Stronger NCA enforcement leads to some reallocation of human capital in our economy. This is because NCA-induced industry changes have detrimental effects on future productivity of inventors. This paper highlights negative consequences of human capital reallocation in response to more labor market regulation.

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Table 1 – Overview of State-Level Changes in Non-Compete Enforceability
This table provides an overview of changes of enforceability of NCAs. The changes are based on Ewens and Marx (2018) as well as Kini et al. (2021). Ewens and Marx (2018) gather data from Malsberger et al. (2016) and consult lawyers. Kini et al. (2021) extend a score of NCA enforceability across states originally developed by Garmaise (2011) to the years 1992-2014. To do so, they use data provided by the law firm Beck Reed Riden LLP. Those two sources together are a comprehensive list of changes during the years 1985-2016. Panel A includes states that increased the enforceability of NCAs. Panel B includes decreases. Panel C includes states that had several changes in the enforceability of NCAs. Brackets in Panel C indicate the direction of the change, (+) equal to an increase in enforceability.

State	Case	Year
Panel A: Increase of Non-Compete Agreement Enforcement		
AL	Alabama legislature	2016
AR	Arkansas legislature	2016
FL	Florida legislature	1996
GA	Georgia legislature	2011
ID	Idaho legislature	2008
MI	Michigan legislature	1985
OH	Lake Land v. Columber	2004
VT	Summits 7 v. Kelly	2005
VA	Assurance Data Inc. v. Malyevac	2013
Panel B: Decrease of Non-Compete Agreement Enforcement		
MT	Wrigg v. Junkermier	2009
NH	New Hampshire legislature	2011
NV	Golden Rd. Motor Inn. v. Islam	2016
OR	Oregon legislature	2008
SC	Poynter Investments v. Century Builders of Piedmont	2010
UT	Utah legislature	2016
Panel C: Repeated In-/Decreases of Non-Compete Agreement Enforcement		
CO	Luncht's Concrete Pumping v. Horner (+)	2011
CO	see Kini et al. (2021) (-)	2013
IL	Fire Equipment v. Arredondo (+)	2011
IL	Fifield v. Premier Dealership Servs. (-)	2013
KY	Gardner Denver Drum v. Peter Goodier and Tuthill Vacuum and Blower Systems (+)	2006
KY	Creech v. Brown (-)	2014
LA	Shreveport Bossier v. Bond (-)	2001
LA	Louisiana legislature (+)	2003
TX	Light v. Centel Cellular (-)	1994
TX	Baker Petrolite v. Spicer (+)	2006
TX	Mann Frankfort Stein & Lipp Advisors v. Fielding (+)	2009
TX	Marsh v. Cook (+)	2012
WI	Star Direct v. Dal Pra. (+)	2009
WI	Runzheimer International v. Friedlen (-)	2015

Table 2 – Summary Statistics
The unit of observation is on an inventor-year level. Variable definitions are provided in the Appendix.

Variable	N	Mean	SD	Min	25%	50%	75%	Max
SIC-4 Industry Change	5,183,982	0.043	0.20	0	0	0	0	1
SIC-3 Industry Change	5,183,982	0.038	0.19	0	0	0	0	1
NAICS-6 Industry Change	5,183,982	0.040	0.19	0	0	0	0	1
NAICS-5 Industry Change	5,183,982	0.038	0.19	0	0	0	0	1
ln(1 + Economic Value of Patents)	5,183,982	0.99	1.46	0	0	0	1.98	9.84
ln(1 + Citation-Weighted Patents)	5,183,982	0.32	0.64	0	0	0	0.37	9.78
Inventor Number Patents	5,183,982	5.55	13.06	0	1	2	5	1,805
Inventor Total Citations	5,183,982	9.78	94.23	0	0.25	1.80	6.86	94,890.93

Table 3 – Baseline Panel Regression: Staggered State-Level Changes in Non-Compete Agreement Enforcement
This table reports the two way fixed effect panel regression of equation 1. The sample is on an inventor-year level. $IndustryChange_{t+1}$ is a dummy variable equal to one if the inventor changes to a firm in a different industry. I split the treatment indicator into $NCAIncrease$ and $NCADecrease$ whether the state decreased, or increased the enforceability of NCAs. In column (1) industry is defined on a SIC 4-digit level, in column (2) on a SIC 3-digit level, in column (3) on a NAICS 6-digit level and in (4) on a NAICS 5-digit level. Variable definitions are provided in the Appendix. Standard errors are clustered by State and Year. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	$IndustryChange_{t+1}$			
	(1)	(2)	(3)	(4)
Panel A: Non-Compete Agreement Enforcement Increase				
$NCAIncrease \times Post$	0.02***	0.02***	0.02***	0.02***
	(3.71)	(3.52)	(3.80)	(3.89)
Observations	5,183,982	5,183,982	5,183,982	5,183,982
R-squared	0.11	0.11	0.12	0.11
Industry Definition	SIC 4-digit	SIC 3-digit	NAICS 6-digit	NAICS 5-digit
Inventor FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Panel B: Non-Compete Agreement Enforcement Decrease				
$NCADecrease \times Post$	-0.00	0.00	-0.00	-0.00
	(0.05)	(0.03)	(-0.04)	(-0.19)
Observations	5,183,982	5,183,982	5,183,982	5,183,982
R-squared	0.11	0.11	0.11	0.11
Industry Definition	SIC 4-digit	SIC 3-digit	NAICS 6-digit	NAICS 5-digit
Inventor FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Figure 1 – Staggered State-Level Changes in Non-Compete Agreement Enforcement: Event Study and Dynamic Effects

This figure reports the result of the difference-in-differences event study of equation 2. The sample is on an inventor-year level. The figure plots the coefficients of pre and post time dummies, interacted with a treatment indicator equal to one if the state increases NCA enforcement. The y-axis shows the coefficient on a regression on the variable $IndustryChange$, which is a dummy variable equal to one if the inventor moves to a firm in a different SIC 4-digit industry in that year. The sample compares treated to never-treated inventors. Inventors are matched based on employment year, number of patents, number of citations and patent technology class. I match the three nearest neighbors with replacement using the Mahalanobis distance. Variable definitions are provided in the Appendix. All regressions include Inventor and Year fixed effects. Standard errors are clustered by Inventor and Year. Confidence intervals are at the 5% level.

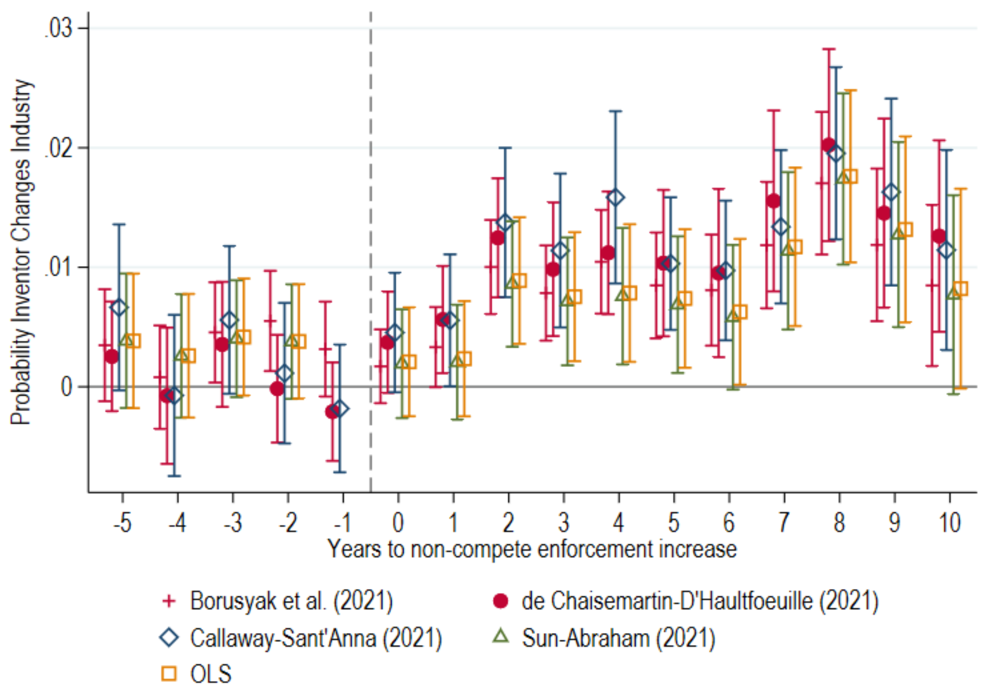


Table 4 – Triple difference-in-differences: Inventors Employed at NCA Firms
This table reports the triple-difference-in-differences fixed effect panel regression of equation 3. The sample is on an inventor-year level. $IndustryChange_{t+1}$ is a dummy variable equal to one if the inventor moves to a firm in a different industry. $NCAIncrease$ is a dummy variable equal to 1 if the state increased the enforceability of NCAs. This variable is interacted with the dummy variable $EmployerNCA$, a proxy for firm-level use of NCA, based on information from form 10-Ks and 10-Qs. The variable is equal to one if the firm states that it relies on NCA or whether senior employees sign NCAs. In column (1) industry is defined on a SIC 4-digit level, in column (2) on a SIC 3-digit level, in column (3) on a NAICS 6-digit level and in (4) on a NAICS 5-digit level. Variable definitions are provided in the Appendix. Standard errors are clustered by Inventor and Year. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	$IndustryChange_{t+1}$			
	(1)	(2)	(3)	(4)
Post	-0.00	-0.00	-0.00	-0.00
	(-1.40)	(-0.33)	(-0.40)	(-0.15)
$NCAIncrease \times Post$	-0.01***	-0.01***	-0.00	-0.00
	(-2.76)	(-3.71)	(-1.38)	(-1.56)
$Post \times EmployerNCA$	0.00	0.00	0.00	0.00
	(1.19)	(1.00)	(0.65)	(0.65)
$NCAIncrease \times Post \times EmployerNCA$	0.02***	0.02***	0.01***	0.01**
	(3.78)	(4.26)	(2.61)	(2.35)
Observations	2,668,634	2,668,634	2,668,634	2,668,634
R-squared	0.14	0.14	0.15	0.14
Industry Definition	SIC 4-digit	SIC 3-digit	NAICS 6-digit	NAICS 5-digit
Inventor FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 5 – NCA Enforceability and Product Market Similarity
This table reports the result of equation 4. The dependent variable is the textual similarity measure of Hoberg and Phillips (2016). The measure captures the similarity between the former and the new employer of each inventor mobility event. $NCAIncrease$ is a dummy variable equal to one if the inventor experienced an increase in NCA enforcement. Variable definitions are provided in the Appendix. Standard errors are clustered by Year. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Product Market Similarity
$NCAIncrease$	-0.02***
	(-11.31)
Observations	158,059
R-squared	0.04
Year FE	YES

Table 6 – Employer NCA Intensity and Inventor-Employer Matching Quality
This table reports the results of equation 4. For Panel A, *EmployerNCA*, a proxy for firm-level use of NCAs, based on information from form 10-Ks and 10-Qs. The variable is equal to one if the firm states that it relies on NCA or whether senior employees sign NCAs. For Panel B, *TechnologyCosineSimilarity* is the cosine similarity between the distribution of patent technology subsections of the inventor and the new employer. I use all previous patents of the inventor up until one year before the move and the last 5 years of patents for the new employer. Variable definitions are provided in the Appendix. *t*-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Panel A: Employer NCA Intensity

Dependent variable:	EmployerNCA
NCAIncrease	-0.05***
	(-2.90)
Observations	37,179
R-squared	0.09
Year FE	YES

Panel B: Technological Similarity

Dependent variable:	Technology Cosine Similarity
NCAIncrease	-0.08***
	(-6.67)
Observations	53,179
R-squared	0.03
Year FE	YES

Figure 2 – Unfamiliar Technology

This figure reports the result of equation 6. The dependent variable of interest is unfamiliar technology class, which is a variable equal to one if the inventor patents in a three digit patent technology class in which she did not patent previously. Variable definitions are provided in the Appendix. All regressions include inventor and year fixed effects. Standard errors are clustered by inventor. Confidence intervals are at the 5% level.

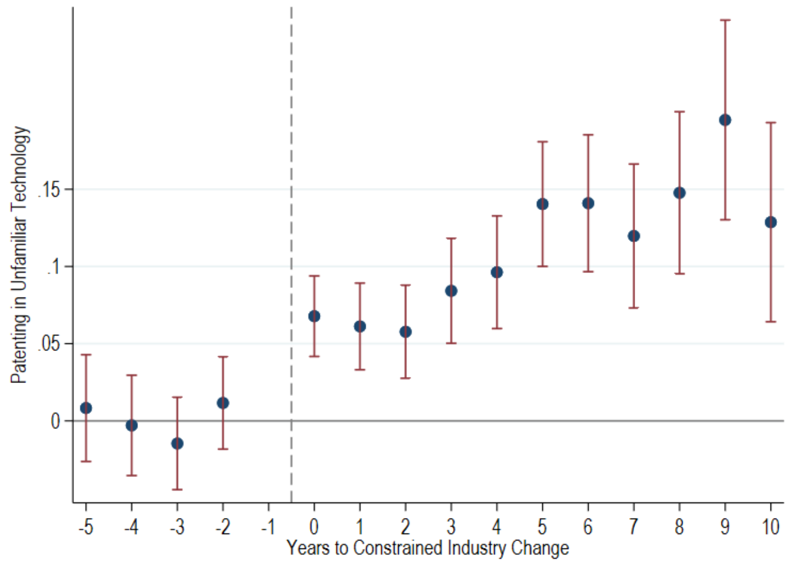


Table 7 – NCA Enforceability and Employment Gap

This table reports the result of equation 7. The dependent variable of interest is employment gap, which is the number of years between two patent filings for each employment move event in the sample. $NCAIncrease$ is a dummy variable equal to one if the inventor moves from a state after an increase in NCA enforcement. $WithinIndustry$ is a dummy variable equal to one if the industry move is within SIC 4-digit industries. Variable definitions are provided in the Appendix. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Employment Gap
$NCAIncrease$	0.89***
	(9.70)
$WithinIndustry$	-0.95***
	(-34.34)
$NCAIncrease \times WithinIndustry$	0.48**
	(2.09)
Observations	263,838
R-squared	0.01
Year FE	YES
State FE	YES

Table 8 – NCA Enforceability Increase and Productivity

This table reports the result of equation 5. The dependent variable of interest is productivity, which captures to what extent the inventor is more productive after changing employers. This variable is measured by economic value of patents and citation-weighted patents following equation 8. $NCAIncrease$ is a dummy variable equal to one if the inventor moves to another firm in another industry after an increase in NCA enforceability. Variable definitions are provided in the Appendix. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Future Productivity (KPSS)	Future Productivity (Citations)
$NCAIncrease$	-0.21***	-0.10***
	(-4.19)	(-3.32)
Constant	0.02	0.26
Observations	24,858	24,858
R-squared	0.00	0.01
Year FE	YES	YES

Table 9 – Inventor Productivity, Technological and Product Market Similarity
This table reports the result of equation 4. The dependent variable of interest is productivity, which captures to what extent the inventor is more productive after changing employers. This variable is measured by economic value of patents and citation-weighted patents following equation 8. $TechDistance$ is a variable which captures the patent technology cosine similarity of inventor and new employer. $ProductDistance$ captures the extent to which the old employer and the new employer are similar to each other following Hoberg and Phillips (2016). Variable definitions are provided in the Appendix. t-statistics are displayed in parenthesis. ***, ** and * represents significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Future Productivity (KPSS)	Future Productivity (Citations)
$TechDistance$	0.35*	0.34***
	(1.80)	(2.78)
$ProductDistance$	0.06*	0.32***
	(1.72)	(14.01)
Observations	18,429	18,429
R-squared	0.00	0.01
Year FE	YES	YES

APPENDIX

A. Variable Definitions

This section provides the variable definitions and the sources of the data.

1. *IndustryChange* – Equal to one if an inventor moves from one firm to another with a different industry classification. Obtained from employment histories of inventors from patentsview.org, patents assigned to corporations from Kogan et al. (2017) and Arora et al. (2021). SIC and NAICS industry codes are obtained from Compustat.
2. *NCA Increase/Decrease* – Equal to one if the state decreased, or increased the enforceability of NCAs. Obtained from Ewens and Marx (2018) and Kini et al. (2021).
3. *EmployerNCA* – Equal to one if the firm has mentioned the use of NCAs either in their annual statement or in employment contracts of senior executives. Obtained from 10-K and 10-Q filings downloaded from EDGAR.
4. *Product Market Similarity* – The cosine similarity of the textual product market descriptions between two listed corporations. Obtained from Hoberg and Phillips (2016) on the Hoberg and Phillips Data Library website:
https://hobergphillips.tuck.dartmouth.edu/
5. *Employment Gap* – The difference in years between two subsequent filing years of two patents. The variable is defined when an inventor moves between two firms.
6. *Patent technology* – The Cooperative Patent Classification (CPC) section was used, which groups patents into 9 different patent sections. Obtained from patentsview.org.
7. *Patent technology subsection* – The Cooperative Patent Classification (CPC) subsection was used, which groups patents into 130 different patent subsections. Obtained from patentsview.org.
8. *Number of patents* – The number of patents of each inventor one year before treatment. Lagged by one year. Obtained from patentsview.org.

9. *Economic Value of Patents, or KPSS* – The economic value of patents, based on stock market reactions to patent grants. Obtained from Kogan et al. (2017), available here:

   https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

10. *Patent Citations* – The number of received (forward) citations of all patents of an inventor one year before treatment. Citations were truncation adjusted using year and technology fixed effects on a patent basis. See Hall et al. (2005) and Lerner and Seru (2021) for details. Obtained from patentsview.org.

11. *Technology Cosine Similarity* – The cosine similarity of the patent technology subsection distributions. The measure includes all previous patents of an inventor and the patents in the last 5 years of the new employer. Obtained from patentsview.org.

12. *Unfamiliar Technology* – A dummy variable equal to one if the inventor did not previously patent in the technology subsection. Obtained from patentsview.org.

13. *Employment Gap* – The difference in years between two subsequent filing years of two patents. The variable is defined when an inventor moves between two firms.

14. *Future Productivity* – Obtained from inventor level regressions. The specification runs separate regressions on each inventor mobility event. The regression includes an inventor fixed-effect as well as a post dummy, which captures the extent to which the inventor is more/less productive after moving to a new employer. Productivity is either measured by the economic value of patents or citation-weighted patents.

15. *Technology Distance* – The cosine similarity of the patent technology subsection distributions. The measure includes all patents in the last 5 years of the old employer and the new employer. Obtained from patentsview.org.

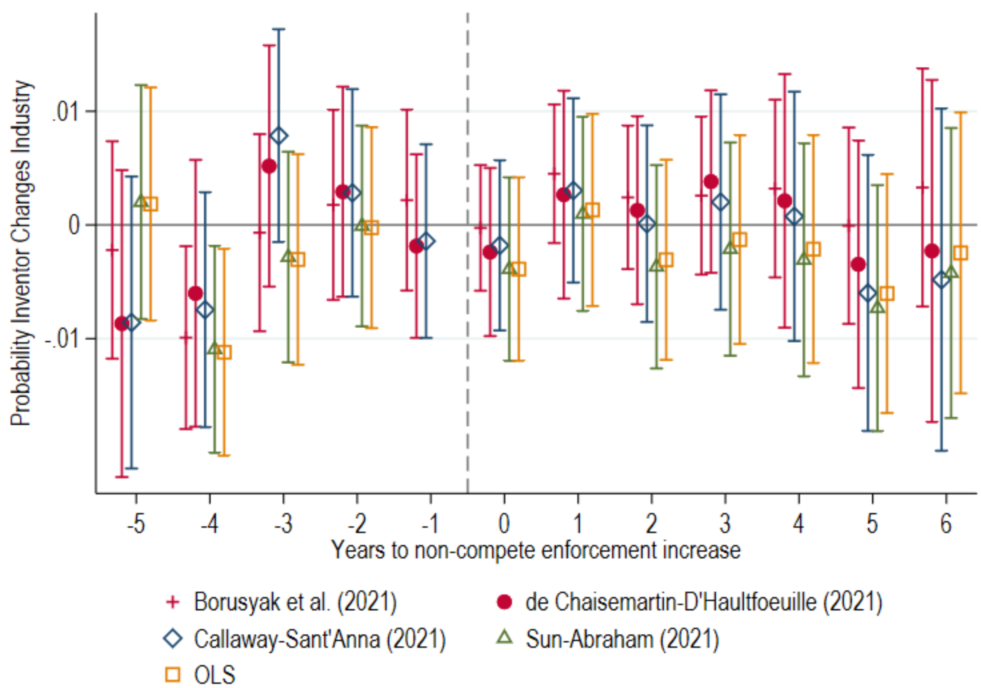
Table A1 – Most Frequent Industry Mobility

This table shows the 5 most common industries ranked according to industry mobility. The table lists the departure industry and the joining industry, a brief description of the industry and the fraction of mobility events compared to the total number of mobility events. Variable definitions are provided in the Appendix.

Rank	Leaving Industry (SIC 3)	Joining Industry (SIC 3)	Fraction
1	Office, Computing, Accounting Mach.	Comp. Programming, Data Process.	4.4%
2	Office, Computing, Accounting Mach.	Electronic Components and Accessor.	3.8%
3	Comp. Programming, Data Process.	Office, Computing, Accounting Mach.	2.4%
4	Electronic Components and Accessor.	Comp. Programming, Data Process.	2.3%
5	Communications Equipment	Electronic Components and Accessor.	2.1%

Figure A3 – Staggered Difference-in-Differences: NCA Enforcement Decreases

This table reports the result of the staggered difference-in-differences event study of equation 2. The sample is on an inventor-year level. The figure plots the coefficient of $NCADecrease$, which is a treatment indicator equal to one for a state that decreases non-compete enforcement. The y-axis shows the effect on the likelihood that an inventor moves across SIC 4-digit industries. The point estimates are normalized to time = -1, the year before treatment. Never-treated inventors are propensity matched based on year, age, number of patents, number of citations and patent technology class. Variable definitions are provided in the Appendix. All regressions include Inventor and Year fixed effects. Standard errors are clustered by Inventor and Year. Confidence intervals are at the top/bottom 5%.



Appendix B: Examples of non-compete agreements

The following are three samples drawn from the sample of innovating firms (those that are assigned patents), of which 54% have references on the use of non-compete agreements. The universe of 10-K and 10-Q filings were obtained from EDGAR and parsed to make them readable using textual analysis.

NUANCE COMMUNICATIONS INC

"In exchange for the severance pay and other consideration under the Severance Agreement to which Executive would not otherwise be entitled, Executive agrees that for a period of one (1) year after the Termination Date, Executive will not, without the express written consent of the Company, in its sole discretion, enter, engage in, participate in, or assist, either as an individual on your own or as a partner, joint venturer, employee, agent, consultant, officer, trustee, director, owner, part-owner, shareholder, or in any other capacity, in the United States of America, directly or indirectly, any other business organization whose activities or products are competitive with the activities or products of the Company then existing or under development. Nothing in this Agreement shall prohibit Executive from working for an employer who is engaged in activities or offers products that are competitive with the activities and products of the Company so long as Executive does not work for or with the department, division, or group in that employer's organization that is engaging in such activities or developing such products. Executive recognizes that these restrictions on competition are reasonable because of the Company's investment in goodwill, its customer lists, and other proprietary information and Executive's knowledge of the Company's business and business plans."

10-Q filing available here:

https://www.sec.gov/Archives/edgar/data/1002517/000100251714000013/nuan12-31x2013ex104.htm

MICROVISION INC

”We also rely on unpatented proprietary technology. To protect our rights in these areas, we require all employees and, where appropriate, contractors, consultants, advisors and collaborators, to enter into confidentiality and non-compete agreements. There can be no assurance, however, that these agreements will provide meaningful protection for our trade secrets, know-how or other proprietary information in the event of any unauthorized use, misappropriation or disclosure of such trade secrets, know-how or other proprietary information.”

10-K filing available here:

https://www.sec.gov/Archives/edgar/data/65770/000113626115000080/body10k.htm

LOCKHEED MARTIN CORPORATION

”This Post Employment Conduct Agreement dated [...] (this “PECA”), together with the Release of Claims being entered into contemporaneous with this PECA, is entered into in consideration of the payment (“Severance Payment”) to be made to me under the Lockheed Martin Corporation Severance Benefit Plan for Certain Management Employees (“Severance Plan”). By signing below, I agree as follows:

Covenant Not To Compete - Without the express written consent of the [Chief Executive Officer/Senior Vice President, Human Resources] of the Company, during the [two/one]-year period following the date of my termination of employment with the Company (“Termination Date”), I will not, directly or indirectly, be employed by, provide services to, or advise a “Restricted Company” (as defined in Section 6 below), whether as an employee, advisor, director, officer, partner or consultant, or in any other position, function or role that, in any such case, oversees, controls or affects the design, operation, research, manufacture, marketing, sale or distribution of "Competitive Products or Services" (as defined in Section 6 below) of or by the Restricted Company [...]"

Exhibit of 10-Q filing available here:

https://www.sec.gov/Archives/edgar/data/936468/000119312508156357/dex107.htm