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Authors
Marx, Matt
Singh, Jasjit
Fleming, Lee

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Regional disadvantage? Employee non-compete agreements and brain drain

Matt Marx[a,*], Jasjit Singh[b], Lee Fleming[c]

[a] MIT Sloan School of Management, 100 Main St., E62-478, Cambridge, MA 02142, United States
[b] INSEAD, 1 Ayer Rajah Avenue, Singapore 138676, Singapore
[c] University of California, Berkeley, 330B, Blum Center, Berkeley, CA 94720, United States

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ABSTRACT

A growing body of research has documented the local impact of employee non-compete agreements, but their effect on interstate migration patterns remains unexplored. Exploiting an inadvertent policy reversal in Michigan as a natural experiment, we show that non-compete agreements are responsible for a "brain drain" of knowledge workers out of states that enforce such contracts to states where they are not enforceable. Importantly, this effect is felt most strongly on the margin of workers who are more collaborative and whose work is more impactful.

1. Introduction

Why has Silicon Valley become the most entrepreneurial area not only in the U.S. but also arguably in the world? More generally, how can policymakers achieve "regional advantage" (Saxenian, 1994) at the sub-national or state level? Understanding the microfoundations of clustering is of interest both to scholars of agglomeration and to policymakers who wish to encourage enterprise and growth. Although natural advantages have been shown to contribute to agglomeration (Ellison and Glaeser, 1999), recent evidence suggests that Marshallian mechanisms such as labor pooling have an even greater effect (Rosenthal and Strange, 2001; Roos, 2005; Ellison et al., 2010). The benefits of labor pooling are often attributed to the interorganizational mobility of workers, which not only facilitates better job matching (Helsley and Strange, 1990) but also encourages individual investment in human capital (Diamond et al., 1990; Rotemberg and Saloner, 2000) given the expanded market for one's expertise and reduced risk of holdup by one's employer. Given that the economic vibrancy of a state and the positive externalities from agglomeration are increasing in the size and quality of its labor pool, it is important to understand factors that shape the dynamics of how the stock of talent in a given state might accumulate or deplete over time.

A high-quality state-level workforce may be built up and maintained in several ways. Unskilled workers may be (re)trained at some expense. Skilled workers not in the state may be enticed to relocate (Bresnahan et al., 2001). Local universities produce high-quality graduates year after year. Most importantly, all of these, as well as skilled workers already working in the state, must be retained. In other words, a key policy challenge, especially in today's knowledge-based economy, is to prevent a "brain drain" of talent. Although the term is most commonly discussed in the context of out-migration from less developed countries to the U.S. or other nations (Kwok and Leland, 1982; Gould, 1994; Grubel and Scott, 1996), talent retention is a priority in advanced economies like the U.S., especially as sub-national regions such as states seek to maintain or enhance their economic competitiveness relative not just to foreign locations but also to one another. Indeed, the fiercest competition for talent may come from not from abroad but from within the same country as domestic relocation is not inhibited by immigration policy. In addition to being an important issue in itself, focusing on intra-national migration provides a cleaner setting for examining the role of migration-related policies more generally.

* Corresponding author. Tel.: +1 6172535539.
E-mail addresses: mmarx@mit.edu (M. Marx), singh@insead.edu (J. Singh), lfleming@berkeley.edu (L. Fleming).

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States within the U.S., although by no means homogenous, are typically more similar than different countries tend to be. This makes it easier to come up with a research design that disentangles migration effects attributable to policy versus those caused by confounding factors like language differences, cultural differences, macroeconomic conditions and immigration restrictions that are naturally more prominent in shaping migration patterns across national borders than state borders.

Skilled workers are essential not only to staff existing firms in the area but also to attract firms outside the state to relocate as well as to facilitate the launch and growth of startups (Zucker et al., 1998). Indeed, tax and other incentives may fall short if businesses worry about the local labor supply. As just one example, Borjas et al. (1992:148) use data from the Current Population Survey to show that Massachusetts “exports its most able workers”. These data are corroborated by a report entitled *Talent Retention in Greater Boston* (Guzzi, 2003), which indicated that “fully half of graduates leave the area after receiving their degrees.” Addressing similar concerns, major cities including Milwaukee, Denver, Tampa, Louisville, Detroit, and Birmingham have launched initiatives designed to entice skilled workers to remain in the state. Noted Tami Door, CEO of the Downtown Denver Partnership, “Before moving or opening an office, companies strongly consider the workforce available in a particular place. Employers will follow the workforce” (Door, 2012). Hence, an understanding of factors that promote (or discourage) the retention of talent—especially actionable policies—may promote economic competitiveness.

Scholars have sought to understand the determinants of within-nation-across-state or “internal” migration at least since Ravenstein’s (1885) exploration of mobility among U.K. workers (see Greenwood, 1997 for a review). Individual characteristics such as age (Plane, 1993) and social connections (particularly among immigrants, see Reher and Silvestre, 2009) as well as regional characteristics including geographic distance (Lansing and Mueller, 1967) and climate (Graves, 1979) play a key role in the relocation decision. A particularly frequent finding within this literature is the role of economic constraints in spurring out-migration. Sjaastad (1962) may have been the first to formally model the decision to emigrate as an investment in one’s human capital, an intuition subsequently borne out in studies using microdata as states with more attractive job prospects enjoy greater in-migration (Treyz et al., 1993; Blackburn, 2010). Moreover, out-migration is not limited to the un(der)employed but rather appears to be increasing in opportunity cost. Better educated and more highly skilled workers are more likely to relocate in response to economic constraints in their current state (Borjas et al., 1992).

Given the responsiveness of talent to relocation incentives, identifying actionable policies to attract and retain key workers would seem a key potential contribution of this literature. But as Greenwood (1997:648) acknowledges, despite several decades of scholarship “few direct links have ever been drawn between policy tools. . .and internal migration”. In this article, we identify an employment policy governed at the state level that might influence interstate migration of skilled workers: the enforcement of employee non-compete agreements. Non-compete agreements are employment contracts that place restrictions on the sorts of jobs ex-employees may take after leaving the firm, usually for a term of 1–2 years. Although companies frequently ask employees to sign non-disclosure agreements that bar them from sharing trade secrets, violations can be difficult to detect whereas it is more straightforward to determine whether an ex-employee joined a competing firm.

Prior work on employee non-compete agreements has focused primarily on how they affect dynamics *within* a state. Using the Current Population Survey, Fallick et al. (2006) found cross-sectional evidence of higher mobility among computer engineers within California, where non-competes are not enforceable. Marx et al. (2009) added causal evidence for within-state mobility using a natural experiment among the larger population of patent-holding inventors. Similar results were recovered by Garmaise (2011) for public-firm executives. That these studies find employee non-compete agreements to be a brake on in-state mobility is particularly significant given that scholars have found interorganizational worker mobility key to the localization of knowledge spillovers. Almeida and Kogut (1999) established strong correlations between in-state mobility of semiconductor engineers and patent citation localization, particularly in California. Similarly, Breschi and Lissoni (2009) found only weak spillover localization in the European biopharmaceutical industry once citations from mobile inventors were excluded. Building on these findings, Belenzon and Schankerman (2013) demonstrated that non-competes lead to fewer local knowledge spillovers within the state.

The in-state implications of employee non-compete agreements are thus well established. Unexplored however is whether non-compete agreements affect the flow of knowledge workers *across states*. In this paper, we argue that highly skilled technical professionals (such as inventors) who live in states where employee non-competes are enforceable have incentives to relocate to states where such agreements are not enforced and their career flexibility is hence less constrained. Within the U.S., employment lawyers routinely counsel clients subject to non-competes to take jobs in states that do not sanction non-competes; moreover, hiring managers and headhunters alike advertise the benefits to prospective employees of working in a state where they are not subject to non-competes (Marx, 2011). Moving to a non-enforcing state in order to avoid a non-compete is facilitated by the “public policy exception” whereby judges are not obligated to uphold out-of-state contracts which would be contrary to the laws of the focal state.[1]

This paper makes two contributions relative to the prior literature. First, we find that enforceable employee non-compete agreements not only reduce within-state mobility among firms (as shown in prior literature) but also induce inventors to exit the state. Moreover, these exiting inventors migrate specifically to states where employee non-compete agreements are unenforceable. Our evidence is based on a difference-in-differences analysis of an inadvertent reversal of non-compete enforcement policy in Michigan, which has been exploited previously but only to analyze within-state trends. The results are not dependent on a particular industry and cannot be recovered in a series of placebo tests.

Second, the “brain drain” driven by employee non-compete agreements is most visible on the margin of workers who are more collaborative and whose work has greater impact. Elite inventors both have higher opportunity costs and may enjoy preferential access to professional opportunities at firms outside the state, which is reflected in their disproportionate likelihood of departing Michigan for non-enforcing states following the policy reversal. While several scholars have explored the impact of non-competes on individual workers (Fallick et al., 2006; Marx et al., 2009; Garmaise, 2011), this paper is the first to show that more valuable workers are more substantially affected by non-competes. Such workers may be particularly painful for a state to lose, given their

[1] The governing case is *Application Group Inc. v. Hunter Group Inc.*, 61 Cal 4th App 881, 72 Cal. Rptr. 2d 73 (1st Distr. 1998), in which an employee of a Maryland firm took a new job in California. Although the employee had been subject to a non-compete, the CA judge refused to enforce the agreement because it violated CA law. Note that although contracts typically stipulate a “choice of law,” in their 1971 *Frame v. Merrill Lynch* ruling (20 Cal. App. 3d 669) the California courts forbade corporations from specifying out-of-state jurisdiction as a means of cherry-picking one’s non-compete enforcement regime.

roles both as "carriers" of the knowledge involved in spillovers and as sources of entrepreneurial activity (Zucker et al., 1998).

Taken together, these results indicate that employee non-compete agreements not only reduce the local circulation crucial to labor pooling and knowledge spillovers, as had been shown previously, but also that such contracts drive an across-state "brain drain" of talent. This paper thus contributes to the literature on the microfoundations of agglomeration (Ellison et al., 2010), highlighting that scholars should consider not only factors affecting the utilization of local resources but also factors that may sap the region of resources. More generally, this work joins with recent scholarship (Belenzon and Schankerman, 2013; Singh and Marx, 2013) in underscoring the importance—despite arguments to the contrary—that states continue to be an interesting and relevant unit of analysis for studying knowledge-related outcomes and related policy examination.

2. Empirical strategy

We present analysis in support of our arguments based upon the U.S. patent record from 1975 to 2005. One approach would be to demonstrate a cross-sectional pattern in which inventors in states that allow enforcement of non-competes are more likely to emigrate, and that emigration is weighted toward moving to non-enforcing states vs. other enforcing states. While such cross-sectional patterns do hold in our data, attaching a causal interpretation is difficult. To more directly get at causality, we employ a difference-in-differences model that exploits a natural experiment arising from an inadvertent reversal of Michigan's non-compete enforcement policy. Michigan's adoption of enforceable non-compete agreements created incentives for inventors to move to states where non-competes were still proscribed. [2] We thus compare *emigration to states where non-competes were proscribed* from Michigan around the time of this policy reversal against a baseline of states that continued to proscribe non-competes throughout the period of our study.

Non-compete enforcement in Michigan had long been prohibited by Public Act No. 329 of 1905, Section 1: "All agreements and contracts by which any person, copartnership or corporation agrees not to engage in any avocation, employment, pursuit, trade, profession or business, whether reasonable or unreasonable, partial or general, limited or unlimited, are hereby declared to be against public policy and illegal and void." In 1985, the Michigan legislature passed the Michigan Antitrust Reform Act (MARA). Although the primary purpose of MARA was to centralize antitrust law, in doing so it repealed numerous statutes including Public Act No. 329, which in its remaining six sections addressed monopoly practices and other antitrust issues. Marx et al. (2009)[3] provide evidence from the legislative record as well as interviews with practicing lawyers active at the time that the change in non-compete policy was inadvertent. Two years later, the legislature instituted a "reasonableness standard" governing the appropriate length and scope of a non-compete. Three aspects of the 1987 action are important. First, it did not reinstate the previous ban. Second, the reasonableness standard—for example, that a term of 10 years would be too long—is common to all U.S. states that do not proscribe non-competes. Third, the reasonableness standard was enacted retroactive to the 1985 passage of MARA. Consequently, the Michigan non-compete policy reversal should be seen as a discrete shift from a full ban prior to 1985 to a post-1985 regime, similar to most other states, where non-competes are permitted.

It might seem unlikely that firms would have implemented non-competes among their employees in Michigan prior to 1985, yet evidence exists that firms frequently have employees sign non-competes even when they are unenforceable under state law. Among firms covered by Execucomp from 1992 to 2004, Garmaise (2011) finds that 58% of those located in California use non-competes even though the state's Business and Professions code Section 16600 has strictly banned the enforceability of non-competes since the 1870s (Gilson, 1999). Kaplan and Stromberg (2003) find similar levels of non-compete use among California entrepreneurs, indicating that not only large, publicly traded firms use non-competes despite legal sanction to the contrary. Thus, although we lack data on the use of non-competes among all firms in Michigan prior to the reform—and we doubt that such data are obtainable—there is strong reason to believe that many Michigan firms had signed non-competes on the books.[4] Given that the repeal of Public Act No. 305 merely removed the ban and did not stipulate any governing timeframe, all such contracts would have become immediately enforceable.

Moreover, the appearance of multiple articles in the *Michigan Bar Journal* (Alterman, 1985; Levine, 1985; Sikkel and Rabaut, 1985) regarding the newfound enforceability of non-competes promoted awareness of the issue, certainly within the community of practicing lawyers and also likely among the leadership of local firms. Lawyers would have transmitted the news to their clients in hopes of generating new contractual and prosecutorial work. Louis Rabaut, a Michigan attorney during the time of MARA, recounted that following the reversal "all of a sudden the lawyers saw no proscription of non-competes. We got active"[5] (Rabaut, 2006).

Importantly, employees' reaction to enforceable non-competes need not be spurred by legal action. In a related field study of workers who left their industry when leaving their jobs, Marx (2011) found only one instance in which the move was prompted by a legal threat (which itself never materialized into a court case). Workers routinely take actions to avoid the potential consequences of non-compete infringement, as was illustrated by an engineer in the internet-search industry we happened to come in contact with. Previously based in New York, he had worked at another internet-search firm when an attractive offer arrived from a competitor with a nearby office. When his former employer verbally threatened him with legal action (though no suit was formally brought) the new employer changed his job offer from its New York office to its California office. "That non-compete," said the engineer in a thick Brooklyn accent, "is the only reason I'm working in California today."

The next section describes the data and empirical approach we use to exploit the inadvertent Michigan policy change as a natural experiment. If non-compete enforcement indeed drives emigration, there should have been an increase in emigration from Michigan to non-enforcing states after the MARA policy change, over and above the baseline temporal pattern of emigration from states that continued not to enforce non-competes throughout

[2] States with statutes limiting the enforcement of employee non-compete agreements during the entire period of this study include AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV (Stuart and Sorenson, 2003).

[3] While Marx et al. (2009) also exploit the Michigan policy reversal as a natural experiment, they use it to establish an intended effect of non-competes: that they bind employees to their employers. By contrast, in this paper we instead examine an *unintended* effect of employee non-compete agreements—that workers leave both the firm and the state. Firms surely do not intend for such contracts to drive some of their most talented employees out of state.

[4] Having employees sign non-competes might appear costly if workers bargained for higher wages in consideration of future employment restrictions. But data from a 2009 survey of IEEE engineers indicated that 70% of the time firms do not ask for the non-compete until after the applicant has accepted the job, restricting the ability of workers to bargain (Marx, 2011).

[5] One might ask whether the change yielded more lawsuits. Databases such as Westlaw record only court *decisions* but not actual cases *filed*. The Courthouse News Service tracks all filed cases but began collecting Michigan data only after 1985.

the period: Alaska, California, Connecticut, Minnesota, Montana, Nevada, North Dakota, Oklahoma, Washington, and West Virginia (Stuart and Sorenson, 2003).

2.1. Sample construction

We analyze interstate mobility by knowledge workers using the U.S. patent database, heuristically identifying patents that belong to the same person in order to construct career histories for 540,780 patenting inventors from 1975 through 2005. In other words, we use patent data not to measure innovation but rather—as several others have—to establish employment histories (Almeida and Kogut, 1999; Trajtenberg et al., 2006; Agrawal et al., 2006; Breschi and Lissoni, 2009). Not all innovative activities are captured by patent records; nonetheless, patenting inventors represent an important category of skilled workers involving the sorts of trade secrets firms seek to protect using non-competes. While the patent database does not exhaustively cover all spans of employment, it nonetheless offers an opportunity to track hundreds of thousands of individuals over long periods of time.

Because the USPTO does not require applicants to supply a unique identifier, it is a non-trivial exercise to reconstruct work histories and co-authorship networks. Fortunately, the patent record contains each inventor's name, hometown, employer, and technology classifications, enabling disambiguation of authorship (for the full algorithm and details, see Li et al.; for earlier approaches, see Trajtenberg et al., 2006). Tracking geographic location across successive patents for these inventors allows us to identify instances of inter-state mobility.[6] Because the exact timing of a move cannot be precisely determined, we use the midpoint of the time window between the last patent in the former state and the first patent observed after the move to a new state to estimate only the year of the move.

Our sample consists of all patents "at risk" of being associated with an interstate mobility event since the previous patent by the same inventor. By construction, an inventor's first patent cannot indicate a move; analysis is therefore restricted only to the inventor's subsequent patents. For the same reason, inventors with only one patent are excluded. We identify *emigration*—workers leaving the state when they change jobs—by a pair of patents belonging to the same inventor where neither the assignees nor the states match. Movement from employment to self-employment (namely, a subsequent patent lacking an assignee) is considered, as firms can enforce non-competes against ex-employees who strike out on their own. Changing from self-employment to employment, however, is not considered, as individuals do not sue themselves for violating a contract. Panel A of Table 1 shows counts of emigration from Michigan to all other U.S. states, by NBER-defined patenting categories.

Importantly, as we are trying to determine whether the imposition of enforceable non-compete agreements led inventors to move to states where such restrictions did not exist, our analysis of emigration includes only moving to states that did not enforce non-competes. To avoid confounding effects of the MARA reform upon the career patterns of inventors, only those inventors active before MARA are included in the analysis. Moreover, although the exogeneity of the Michigan policy reversal is attractive for purposes of identification, an ideal analysis would feature a set of treated and control observations that are perfectly matched along covariates. Such a sample is difficult to obtain from observational data, but we use Coarsened Exact Matching (Iacus et al., 2009) to improve covariate balance between the treatment group of Michigan inventors and the control group of inventors in states that continued not to enforce non-compete agreements. In addition to reducing model dependence, improved balance renders univariate analysis more informative. Our matching criteria include the inventor's patenting rate, the (logged) number of patents belonging to the firm to which the inventor's prior patent was assigned, the interval between the inventor's patents, the inventor's first patenting year, and the percentage of an inventor's patents that were in the automotive sector. All are measured strictly on a pre-MARA basis. Rather than assign arbitrary cut points, we relied on the Coarsened Exact Matching implementation in Stata to algorithmically determine the matching "bins" in order to optimize an objective function.[7] Panel B of Table 1 provides descriptive statistics for the CEM-matched sample.

2.2. Econometric model

We estimate a logistic model of the likelihood that a given patent *i* indicates that its inventor *j* emigrated to a non-enforcing state. Letting E_{ij} indicate emigration, $\boldsymbol{X}_{ij}$ a vector of covariates of the patent, $\boldsymbol{Z}_i$ a vector of time-independent covariates of the inventor, and $\boldsymbol{W}_{it}$ a vector of time-varying covariates of the inventor, the estimation equation is therefore $Pr(E_{ij}=1) = e^{(\beta \boldsymbol{X}ij+\gamma \boldsymbol{Z}i+\lambda \boldsymbol{W}it)} / (1+e^{(\beta \boldsymbol{X}ij+\gamma \boldsymbol{Z}i+\lambda \boldsymbol{W}it)})$. Each patent is taken as an observation, with the regression analysis reporting robust standard errors clustered by inventor to account for non-independence of observations.[8] Observations are weighted based on the number of matched control observations found for each focal observation. All models are estimated using Stata 10.

The key variable of interest in our difference-in-differences analysis is the interaction of the indicators for Michigan residence and the post-MARA time period, after these two indicators have also been entered directly in the model to capture the baseline effects. Time-varying control variables include annual indicators, the number of patents the inventor had been granted in the pre-MARA period (logged), the number of days since the preceding patent by this inventor (logged), and whether the inventor had previously emigrated. We also account for characteristics of the last patent prior to the inventor's move using indicators for six top-level technical classifications to which the prior patent was assigned (Hall et al., 2001) and the logged number of patents belonging to the firm to which the prior patent was assigned (as a proxy for firm size). Given the over-representation of the automotive industry in Michigan (Singleton, 1992), we include an indicator for automotive patents as well.

3. Results

Descriptive data in Table 2 illustrates a brain drain from Michigan to non-enforcing states following the 1985 MARA policy reversal: during a symmetric window from 1975 to 1996 surrounding MARA, the rate of emigration to non-enforcing states grew in Michigan (0.24–0.32%) while dropping in states that did not enforce non-competes (0.20–0.13%). The relative risk of post-MARA emigration was 1.35 in Michigan, twice as high as in states that continued not to enforce non-competes (where the relative risk of post-MARA emigration was 0.68). Moreover, emigration trends are

[6] We detect mobility only in instances where an inventor files for a patent both before and after a move. Moves in our study are, in any case, only a subset of all moves involving skilled workers (patenting or not).

[7] Stringent matching naturally comes at the cost of fewer (50.1%) treated observations being matched to control-group observations. To ensure that our findings are not overly sensitive to this, we carried out analysis with less stringent matching of 20 bins per continuous variable, matching a much higher fraction (95.7%) of treated observations but yielding similar results.

[8] Clustering standard errors at the state level yields similar results, as did clustering simultaneously on inventor and state, though the latter procedure in Stata does not permit weights and thus is not used as our preferred specification.

Table 1
Panel A: Emigrating inventors from Michigan to other states, by NBER-defined patent category.

	Chemical	Computers and Communication	Drugs and Medical	Electrical and Electronic	Mechanical	Other	Total
AL	4	1	2	0	2	5	14
AR	0	0	0	0	0	1	1
AZ	3	0	0	1	8	10	22
CA	45	9	10	39	45	39	187
CO	6	7	0	7	5	3	28
CT	7	0	0	3	10	12	32
DC	1	0	3	0	1	0	5
DE	3	1	0	0	0	0	4
FL	10	8	3	10	29	31	91
GA	4	0	0	2	7	18	31
HI	0	0	0	0	1	1	2
IA	1	0	1	2	5	3	12
ID	1	0	0	0	1	3	5
IL	21	3	7	13	14	19	77
IN	25	5	9	15	36	14	104
KS	2	0	0	0	0	4	6
KY	3	2	1	1	7	4	18
LA	25	0	1	0	3	1	30
MA	14	1	10	5	15	7	52
MD	6	1	2	2	4	5	20
ME	0	0	0	0	0	1	1
MN	13	3	6	4	12	11	49
MO	10	0	8	2	10	9	39
MS	8	1	0	3	3	4	19
MT	0	0	1	0	1	0	2
NC	11	2	2	6	6	13	40
ND	1	0	0	0	0	1	2
NE	1	0	0	1	2	1	5
NH	2	0	0	2	2	1	7
NJ	26	0	6	9	12	5	58
NM	1	1	0	1	2	2	7
NV	0	0	0	0	1	2	3
NY	16	0	2	8	16	15	57
OH	39	4	10	17	44	32	146
OK	8	1	1	2	1	2	15
OR	4	1	0	4	0	2	11
PA	33	2	4	7	17	21	84
RI	1	0	0	0	2	2	5
SC	2	1	0	2	11	14	30
SD	0	1	0	0	0	0	1
TN	2	0	2	0	12	5	21
TX	31	1	5	9	30	18	94
UT	4	0	0	4	1	1	10
VA	3	1	1	0	8	8	21
VT	1	0	0	0	0	0	1
WA	4	2	1	4	6	2	19
WI	5	3	1	9	9	8	35
WV	1	0	0	0	0	3	4
Total	408	62	99	194	401	363	1527

Panel B: Descriptive statistics for patent sample used for analysis of domestic emigration, 1975–1996

		Mean	Std dev	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Patent indicates emigration from previous state	0.002	0.046	0.000	1.000	1.000									
(2)	Days since last patent (ln)	5.251	2.239	0.000	8.995	0.046	1.000								
(3)	Inventor had emigrated previously	0.007	0.081	0.000	1.000	0.057	−0.027	1.000							
(4)	Prior employer's number of patents (ln)	3.297	2.172	0.000	8.673	−0.013	−0.182	0.018	1.000						
(5)	Inventor's pre-MARA patenting rate	0.512	0.284	0.134	1.684	−0.016	−0.175	−0.010	0.195	1.000					
(6)	Auto industry	0.013	0.111	0.000	1.000	0.000	0.014	−0.003	−0.010	−0.027	1.000				
(7)	Michigan	0.333	0.471	0.000	1.000	0.005	0.019	−0.056	0.098	−0.016	0.076	1.000			
(8)	Post-MARA	0.403	0.490	0.000	1.000	−0.007	−0.041	0.076	0.063	0.169	−0.003	−0.071	1.000		
(9)	Number of pre-MARA patents	1.294	0.635	0.693	4.043	0.000	−0.108	−0.001	0.156	0.274	−0.003	0.106	−0.211	1.000	
(10)	In largest national component	0.180	0.384	0.000	1.000	0.000	−0.115	0.002	0.482	0.248	−0.026	0.068	0.009	0.271	1.000

Notes: Panel A. Patent categories are defined by Hall, et al. (2001) and are determined by the inventor's Michigan patent prior to the move. Data in this table are inclusive of the years 1975–2005. Panel B. Observations are restricted to those inventors in Michigan as well as states that continued not to enforce non-competes (AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV). Observations are matched using Coarsened Exact Matching. n = 23,351 patents.

Table 2
Domestic emigration from Michigan vs. states that do not enforce non-competes.

	Pre-MARA	Post-MARA	Relative risk
Michigan	0.24%	0.32%	1.353
non-Michigan	0.20%	0.13%	0.677
Michigan % increase over non-Michigan			*99.9%*

Notes: Observations are restricted to those inventors in Michigan as well as states that continued not to enforce non-competes: AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV. Thus emigration is observed *only to states that do not enforce non-competes*. Observations are matched using Coarsened Exact Matching. $n = 23{,}351$ patents.

similar between Michigan and the control states in the pre-MARA period (0.24% vs. 0.20%).

This effect is also obtained via multivariate logistic analysis. Table 3 assesses the impact of the policy reversal in a series of progressively longer intervals surrounding MARA. We start with the 1983–1988 time period in model (1) given that the reform was passed in 1985 and may have taken some time to diffuse as lawyers learned of the reversal and informed their clients. We then examine models in two-year increments thereafter until the widest possible symmetric window given the data (1975–1996, in model (5)). In each of these models, including the three-year symmetric window surrounding the policy reform in model (1), statistically and economically significant evidence is found for a "brain drain" from Michigan to states that did not enforce non-compete agreements. For the remainder of our analysis, we use the widest window in model (5). In this model, the coefficient on the interaction of the Michigan and the post-MARA indicators is statistically significant at the 1% level.

Following Greene (2009), we assess the magnitude of the effect by calculating the predicted probability of emigration to non-enforcing states for various values of the explanatory variables while holding other covariates at their means. As both of the variables in our interaction term are dichotomous, instead of constructing a graph we compute the change in relative risk of emigration to non-enforcing states using predicted probabilities from the table, essentially reconstructing the components of Table 2 from the regression. From model (5) of Table 3, the predicted probability of emigration to non-enforcing states for non-Michigan inventors is 0.04% before MARA and 0.07% thereafter. Similarly, the predicted probability of emigration to non-enforcing states for Michigan inventors is 0.04% before MARA and 0.31% afterward. Thus the relative risk of post-MARA emigration to non-enforcing states versus pre-MARA emigration to non-enforcing states is 7.24 for Michigan inventors and 1.58 for non-Michigan inventors.

In the final model of Table 3, we establish that the brain drain was not just a manifestation of a general exodus from Michigan which might be unrelated to the non-compete enforcement policy. We do so by showing that the brain drain was channeled into states that continued not to enforce non-competes and thus became more attractive labor markets for workers following Michigan's inadvertent adoption of non-compete enforcement. Specifically, model (6) presents a multinomial analysis relative to not moving. The first column of model (6) corresponds to the outcome of the prior models: emigrating to states that continued not to enforce non-competes. The second column of model (6) corresponds to the complementary outcome of emigrating to the 39 states that enforced non-compete agreements throughout 1975–1996 (i.e., the inverse of the control group). Consistent with the mechanism behind the brain drain result being non-compete enforcement policy, model (6) shows evidence of increase emigration to non-enforcing states and decreased emigration to enforcing states.[9]

[9] In unreported models, we find that emigration out of Michigan was not offset by immigration into the state, so the effects reported here are indicative of a net loss of inventors.

3.1. Robustness and placebo tests

In Table 4, we subject the brain drain result to a number of additional tests. First, we examine whether the effect is driven primarily by migration to California. While such a finding would not necessarily rule out the importance of non-compete enforcement policy, one might be concerned that our results merely constitute a "California effect," for at least three reasons. First, given that California's Business and Professions code Section 16600 is the longest-standing prohibition against non-compete enforcement (arguably as strict as Michigan's Public Act 305 of 1905 yet dating back to 1872—see Gilson, 1999), Michigan inventors seeking jobs elsewhere might have particularly targeted California rather than the emigration patterns being more general. Second, given the state's extensive landmass (and, more broadly, other natural factors including attractive weather), California might offer a disproportionate number of relocation opportunities. Third, the entrepreneurial dynamics of Silicon Valley may have been attractive to many of the inventors in this study. The analysis reported in model (1) shows that the brain drain finding is not driven primarily by an exodus of Michigan inventors to California in the post-MARA period. In this model, we exclude all emigration to California, which reduces the number of observations but retains statistical significance on the key interaction term. Moreover, the magnitude of the coefficient on Michigan * post-MARA in model (1) of Table 4 closely resembles that in model (5) of Table 3.

In the next three models, we address the possibility that the brain drain is explained by industry mix. Although our previous models controlled for automotive patents, in model (2) we explore whether the decline of other industries in Michigan could have been responsible. For each of the 36 industry subcategories defined by Hall et al. (2001), we analyze the growth or decline in Michigan patenting during our sample window, using a three-year running average. Starting with a sample drawn from the 22 subcategories with a greater than 1% share of Michigan patenting, we label the bottom quartile as "declining" Michigan industries[10] and exclude them from model (2). If these declining industries were responsible for the brain drain, we would not expect to see a positive and significant coefficient on the interaction of Michigan and post-MARA. But the previous finding still holds (with magnitude similar to that found in model (5) of Table 3), suggesting that inventors even in vibrant and growing industries departed Michigan for non-enforcing states following MARA.

Even if inventors were not "pushed" to emigrate from industries that were declining in Michigan, one might have the complementary concern that they were "pulled" by attractive opportunities in industries that were growing quickly outside of Michigan. In model (3), we repeat the exercise but instead identify the top quartile of industries according to their patenting growth in the control states.[11] Excluding these from the model restricts our analysis to industries in the control states that were growing less slowly, where we would not expect to see a positive and significant coefficient if inventors were merely leaving Michigan for attractive industries in non-enforcing states. But model (3) shows that emigration from Michigan to non-enforcing states was not limited to industries that were growing rapidly in the control states. Additionally, model (4) includes state-industry fixed effects to absorb further variation, with consistent results. Taken together, these

[10] The bottom quartile of MI growth industries are Mechanical, Agriculture, Organic Compounds, Other (misc.).

[11] The top quartile of growth industries in the control states are semiconductor devices, communications, information storage, measuring and testing, and drugs and medical (misc.).

Table 3
Difference-in-differences logistic regressions of domestic emigration to non-enforcing states with symmetric time windows about MARA at two-year intervals.

Window surrounding MARA DV = moves to (non-) enforcing state	(1) 1983–1988	(2) 1981–1990	(3) 1979–1992	(4) 1977–1994	(5) 1975–1996	(6) 1975–1996	
	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Enforcing
Michigan * post-MARA	3.5486**	2.7578***	1.5546*	1.4307**	1.5194**	0.7607*	−0.3358*
	(1.3146)	(0.8026)	(0.6053)	(0.5092)	(0.4749)	(0.371)	(0.159)
Michigan	−0.4905	−0.2022	0.0864	0.1162	0.0259	−0.4996**	−0.0064
	(0.5749)	(0.4065)	(0.3703)	(0.3344)	(0.3223)	(0.168)	(0.098)
Post-MARA	−2.7983**	−1.7065	−2.0315	−1.0651	−0.8453	−1.0923	−1.0039*
	(1.0617)	(1.1019)	(1.3440)	(0.7659)	(0.7726)	(0.645)	(0.428)
Days since last patent (ln)	0.7152*	0.8658***	0.8196***	0.8616***	0.8780***	1.0136***	0.9823***
	(0.2876)	(0.2384)	(0.2061)	(0.1710)	(0.1623)	(0.130)	(0.066)
Inventor had emigrated previously	1.5412	2.8531***	2.9092***	3.3181***	3.2777***	2.5522***	1.9772***
	(1.3707)	(0.8636)	(0.6541)	(0.4476)	(0.4531)	(0.191)	(0.128)
Prior employer's number of patents (ln)	0.0002	0.0185	−0.0254	−0.0490	−0.0887	−0.1299***	−0.1793***
	(0.1061)	(0.0786)	(0.0737)	(0.0589)	(0.0570)	(0.033)	(0.021)
Inventor's pre-MARA patenting rate	−0.1322	0.3681	0.6034	0.3145	0.3921	0.4954**	0.3358***
	(1.5481)	(1.1217)	(1.0202)	(0.8243)	(0.7462)	(0.185)	(0.102)
Auto industry		0.7679	0.4435	−0.3377	−0.4147	−0.2419	−1.6411*
		(1.0214)	(1.0596)	(1.2728)	(1.1972)	(1.032)	(0.713)
Constant	−9.8171***	−12.1163***	−12.2614***	−11.8302***	−11.5732***	−11.6270***	−10.0993***
	(2.8805)	(2.8719)	(2.6316)	(2.0885)	(1.8583)	(1.061)	(0.577)
Observations	6285	10,038	15,499	20,714	23,351	59,396	59,396

Notes: The dependent variable is the likelihood that a given patent indicates domestic emigration to non-enforcing states (AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV), for U.S. inventors in Michigan or other non-enforcing states. All models include year, industry, and first-patent-year cohort indicators. Data are matched by Coarsened Exact Matching. Robust standard errors are in parentheses, clustered by inventor. The auto-industry indicator is dropped in the narrowest window as a perfect predictor.

* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Table 4
Robustness checks and placebo tests for difference-in-differences logistic regressions of domestic emigration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Michigan * post-MARA	1.8777**	1.7871***	1.3219*	2.4726*	0.5102	−0.6289	0.7117	0.8306
	(0.6503)	(0.528)	(0.590)	(1.016)	(0.4229)	(0.4750)	(0.5162)	(0.4932)
Michigan	−1.4908**	−0.0356	0.2018		1.1641***	0.4237	0.1367	0.2825
	(0.4697)	(0.333)	(0.356)		(0.2451)	(0.3088)	(0.3623)	(0.3090)
Post-MARA	−0.3465	−0.9946	−0.8826	−1.2618	−0.8558	1.3276	−0.9136	−0.8618
	(0.8819)	(0.785)	(0.972)	(1.028)	(0.7526)	(1.0165)	(0.7816)	(0.7679)
Days since last patent (ln)	0.7899***	0.9172***	0.8999***	0.8735***	0.8672***	0.2728***	0.8259***	0.8789***
	(0.2092)	(0.164)	(0.160)	(0.153)	(0.1686)	(0.0684)	(0.1588)	(0.1512)
Inventor had emigrated previously	3.0940**	3.1315***	3.2912***	3.3673***	0.5574	3.2364***	3.2504***	3.4852***
	(1.0065)	(0.482)	(0.536)	(0.562)	(0.6518)	(0.4307)	(0.4726)	(0.3970)
Prior employer's number of patents (ln)	−0.2648***	−0.0948	−0.1374*	−0.0847	2.1633***	0.1981**	−0.0567	−0.0678
	(0.0793)	(0.061)	(0.064)	(0.055)	(0.2881)	(0.0622)	(0.0573)	(0.0582)
Inventor's pre-MARA patenting rate	1.0686	0.3610	0.1528	0.5454	−0.0984*	−0.7391	0.2553	0.3032
	(1.1426)	(0.777)	(0.822)	(0.814)	(0.0482)	(0.6356)	(0.7782)	(0.7232)
Auto industry		−0.2660	−0.3097	−0.5899	0.2436	1.0405	−0.2465	−0.3715
		(1.181)	(1.304)	(1.264)	(0.2520)	(0.9540)	(1.1498)	(1.1785)
Constant	−10.1128***	−11.7250***	−11.5754***	−28.4934***	−10.2019***	−7.7331***	−11.6309***	−11.5669***
	(2.0500)	(1.617)	(1.947)	(2.099)	(1.4806)	(1.5826)	(2.0009)	(1.7762)
DV=	Emigration	Emigration	Emigration	Emigration	Emigration	Within-firm transfers	Emigration	Emigration
Treatment state	Michigan	Michigan	Michigan	Michigan	Ohio	Michigan	Michigan	Michigan
Control group	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing	Non-enforcing
Excludes California	Yes	No	No	No	No	No	No	No
Industries	All	Non-declining In MI	Non-growth Outside MI	All	All	All	All	All
State-industry fixed effects	No	No	No	Yes	No	No	No	No
MARA year	1985	1985	1985	1985	1985	1985	1984	1986
Observations	12,208	20,601	20,578	21,135	24,494	23,351	23,351	23,351

Notes: Observations are for patenting U.S. inventors in Michigan or other non-enforcing states (AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV), 1975–1996. All models include year, industry, and first-patent-year cohort indicators. Robust standard errors are in parentheses, clustered by inventor. The auto-industry indicator is dropped in model 2 due to perfect prediction as those in the auto industry who emigrated from Michigan went exclusively to California.

* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

Table 5
Domestic emigration to non-enforcing states for inventors, by a median split of human and social capital. In these tables, “non-Michigan” refers to the non-enforcing control states AK, CA, CT, MN, MT, NV, ND, OK, WA, and WV.

Panel A: Full sample including Michigan and all control states

Median and below				Above median			
	Pre-MARA	Post-MARA	Relative risk		Pre-MARA	Post-MARA	Relative risk
Citations per patent							
Michigan	0.20%	0.33%	1.625	Michigan	0.27%	0.31%	1.134
Non-Michigan	0.13%	0.14%	1.112	Non-Michigan	0.26%	0.10%	0.395
Michigan % increase over non-Michigan			*46.1%*	*Michigan % increase over non-Michigan*			*186.8%*

Median and below				Above median			
	Pre-MARA	Post-MARA	Odds ratio		Pre-MARA	Post-MARA	Odds ratio
Number of collaborators							
Michigan	0.25%	0.22%	0.870	Michigan	0.21%	0.51%	2.388
Non-Michigan	0.17%	0.11%	0.635	non-Michigan	0.29%	0.20%	0.710
Michigan % increase over non-Michigan			*37.0%*	*Michigan % increase over non-Michigan*			*236.3%*

Panel B: Restricted sample excluding California and Connecticut from the control states

Median and below				Above median			
	Pre-MARA	Post-MARA	Relative risk		Pre-MARA	Post-MARA	Relative risk
Citations per patent							
Michigan	0.10%	0.10%	1.067	Michigan	0.08%	0.15%	1.768
Non-Michigan	0.29%	0.24%	0.852	Non-Michigan	0.52%	0.52%	1.004
Michigan % increase over non-Michigan			*25.2%*	*Michigan % increase over non-Michigan*			*76.0%*

Median and below				Above median			
	Pre-MARA	Post-MARA	Odds ratio		Pre-MARA	Post-MARA	Odds ratio
Number of collaborators							
Michigan	0.13%	0.05%	0.354	Michigan	0.05%	0.18%	3.680
Non-Michigan	0.38%	0.21%	0.558	Non-Michigan	0.48%	0.51%	1.059
Michigan % increase over non-Michigan			*−36.5%*	*Michigan % increase over non-Michigan*			*247.6%*

Notes: The emigration rate out of Michigan is affected by their exclusion because many Michigan inventors moved to either CA or CT.

models indicate that the brain drain was not solely driven by growing or declining industries.

The next two models address the concern that the observed brain drain might not be unique to Michigan but possibly an artifact of more general patterns of migration. The placebo test in model (5) treats inventors in Ohio as the experimental group. Like Michigan, Ohio is a medium-sized Midwestern state that experienced a declining economy in the later 1980s and early 1990s. If the brain drain were merely a result of general migration patterns, we would expect to see Ohio inventors likewise moving to non-enforcing states. But no statistically significant evidence of a brain drain out of Ohio is obtained in model (5). We repeated the Ohio placebo test for every U.S. state with at least 1% of nationwide patenting activity;[12] none of these produced a positive coefficient on the interaction term with statistical significance at conventional levels.

In model (6), we dig deeper into the possibility that the brain drain is an artifact of general patterns of relocation and migration not related to non-competes. We change our dependent variable from interstate moves for new employers to interstate moves within the same firm—in other words, while being transferred by one’s employer to an office in another state. We would not expect non-competes to affect those who remain with their current employer and indeed find no evidence that Michigan inventors were more likely to be transferred across state lines by their employers following the policy reversal.

Models (7) and (8) assess the importance of the timing of the MARA policy reversal in 1985 in order to address the potential concern that the labor flows observed in this regression are coincident with longer-term transfers of talent from Michigan to the control states and have little to do with the MARA policy reform of 1985. We perform two placebo regressions, one where the policy reversal occurs in 1984 and one in 1986. Neither moving the reform date back one year in model (7) nor moving the date of MARA in model (8) ahead one year produces strong evidence of a brain drain. An additional unreported model executes the block-bootstrap as advised by Bertrand et al. (2004) in order to account for serial correlation in difference-in-differences models with a large number of periods.

Finally, unreported nationwide analysis available from the authors provides additional evidence that the emigration from enforcing states to non-enforcing states is not unique to Michigan. While cross-sectional analysis is obviously subject to concerns about unobserved heterogeneity, consistency of this cross-sectional finding with the results above derived from the natural experiment from the Michigan context is reassuring.

3.2. *Moderating effects for collaborative and impactful knowledge workers*

We have shown that the brain drain induced by non-competes is not specific to particular industries. But are the effects felt equally among all types of workers? In this section, we examine inventors with varying levels of impact and collaborativeness we can derive from patent data. We use average citations to pre-MARA patents (in a fixed five-year window) as a measure of the quality and impact of an inventor’s prior work. Since highly cited patents have been shown to be more valuable technically, economically, and socially (Trajtenberg, 1990), inventors with these patents are likely to be

[12] States with at least 1% of nationwide patenting activity are AZ CA CO CT FL IL IN MA MD MI MN MO NC NJ NY OH OK PA SC TX VA WA WI.

Table 6
Difference-in-differences analysis of domestic emigration differences for inventors, by citations per patent and number of collaborators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Citations per patent				Number of collaborators			
	Above median	Below median	Above median (no CA or CT)	Below median (no CA or CT)	Above median	Below median	Above median (no CA or CT)	Below median (no CA or CT)
Michigan * post-MARA	1.9696*	1.2806	1.7743*	2.2983	1.6609**	1.2772	2.7794**	1.1238
	(0.904)	(0.699)	(0.860)	(1.498)	(0.643)	(0.721)	(1.001)	(1.505)
Michigan	0.0528	0.0634	−1.9631**	−1.716	−0.2100	0.0842	−2.7234**	−1.5517*
	(0.388)	(0.557)	(0.619)	(1.031)	(0.466)	(0.427)	(0.893)	(0.749)
Post-MARA	−17.2553***	−0.5175	−0.0754	−0.5385	−0.8423	−0.4812	2.3482	−1.1246
	(1.195)	(1.007)	(1.261)	(1.114)	(0.855)	(1.350)	(1.406)	(4.318)
Days since last patent (ln)	1.1013***	0.6382***	0.7959**	0.6467*	0.7813***	1.0719***	0.5333*	1.2609**
	(0.227)	(0.166)	(0.286)	(0.277)	(0.224)	(0.209)	(0.223)	(0.404)
Inventor had emigrated previously	2.4897**	3.5876***	3.0379*	1.2000	3.0475***	1.9542	2.6669**	
	(0.772)	(0.578)	(1.372)	(1.390)	(0.573)	(1.267)	(0.957)	
Prior employer's number of patents (ln)	−0.0191	−0.1541	−0.1078	−0.4535*	−0.0259	−0.1414	−0.1826	−0.1925
	(0.081)	(0.081)	(0.086)	(0.187)	(0.079)	(0.091)	(0.113)	(0.150)
Inventor's pre-MARA patenting rate	0.3321	0.2251	0.8202	3.9135*	0.6444	−0.9706	2.3482	−1.1246
	(1.077)	(1.090)	(1.322)	(1.756)	(0.888)	(1.491)	(1.406)	(4.318)
Auto industry		0.0796		1.7598*		0.4257		
		(1.505)		(0.754)		(1.053)		
Exclude California and Connecticut?	No	No	Yes	Yes	No	No	Yes	Yes
Constant	−12.0385***	−9.2847***	−11.8498***	−7.3185**	−12.0285***	−10.8265***	−8.7701***	−28.9845
	(1.994)	(1.652)	(2.526)	(2.434)	(2.094)	(2.142)	(2.240)	(0.000)
Observations	7991	11,405	3689	6088	6387	12,969	968	2524

Notes: Observations are patenting U.S. inventors in Michigan or other non-enforcing states, 1975–1996. All models include year, industry, and first-patent-year cohort indicators. Data models are matched using Coarsened Exact Matching. Robust standard errors are in parentheses, clustered by inventor. The auto-industry indicator is dropped in some models as a perfect predictor.

* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

more valuable to a firm or state. Likewise, we use the number of pre-MARA co-authors as a measure of propensity to collaborate and thus an indicator of social capital. Collaborative linkages have been shown to increase knowledge diffusion, both within and across firms (Singh, 2005), so inventors with more of such linkages are likely to be more valuable in generating knowledge spillover benefits for a state.

Descriptive data in Panel A of Table 5 show that the relative risk of post-MARA emigration to non-enforcing states by inventors with impactful work—i.e., those with greater-than-median citations per patent prior to the policy reversal—was 186.8% higher in Michigan than in the control states. By contrast, the relative risk of post-MARA emigration to non-enforcing states by Michigan inventors at or below the median number of citations per patent was only 46.1% higher than their peers in states that continued not to enforce non-competes. This is consistent with a view that elite inventors—those that produce high-impact inventions—have higher opportunity costs. They would therefore be more motivated to seek employment in less restrictive states, just as Ganco et al. (2014) find that more highly skilled workers were more likely to leave U.S. semiconductor firms that sued aggressively to enforce patent protection. Moreover, such inventors should be more attractive to out-of-state employers and thus more likely to be recruited. Consequently, more impactful workers may be at once more eager and more able to emigrate once employee non-compete agreements are enforced locally.

Panel A of Table 5 also shows that the relative risk of post-MARA emigration to non-enforcing states by more connected inventors—namely, those with more than the median number of patent co-inventors prior to the policy reversal—was 236.3% higher in Michigan than elsewhere. By contrast, the relative risk of post-MARA emigration to non-enforcing states by Michigan inventors at or below the median number of co-authors was only 37.0% higher than their peers in states that continued not to enforce non-competes. (As with the above measures, the number of collaborative linkages for an inventor was measured strictly on a pre-MARA basis.) More collaborative inventors should be more likely to emigrate to non-enforcing states for at least three reasons. First, they are more likely to hear about job opportunities through their collaborative ties. Second, they are more likely to be known outside their firm and to receive outside offers of employment. Third, given trends in collaborative invention and the apparent greater productivity of teams (Wuchty et al., 2007), collaborative inventors are more likely to be valued by outside employers.

We note that in this analysis, emigration of highly cited and highly collaborative inventors in the control states was not constant but dropped significantly following MARA. This raises a question regarding whether our estimated effects are driven by the policy change in the treatment state or by something we do not capture regarding the control states. In calculations available from the authors, we observed that the drop in emigration rates is driven most prominently by California and Connecticut, two control states jointly responsible for more than half of patenting and each of which saw an emigration drop of approximately 20%. When we exclude California and Connecticut in Panel B of Table 5, emigration levels in the control states are similar pre- and post-MARA and our results continue to hold.

For multivariate analysis, we present split-sample analyses in Table 6 of the likelihood of emigration to non-enforcing states by inventors with varying levels of collaboration and impact. Models (1–4) explore the dimension of citation-based impact, and models (5–8) explore collaboration. Those with above-median citations per patent exhibit economically and statistically stronger emigration to non-enforcing states in model (1) than those below the median in model (2). A similar pattern emerges for the number of past collaborative ties: both the magnitude and statistical significance of the interaction term are stronger for those with an above-median number of collaborators in model (5) than for those with below-median number of collaborators in model (6). Similar patterns are obtained in models (3–4) and (7–8) when excluding California and Connecticut. Thus the brain drain appears to be most pronounced among those who are more collaborative and whose work has greater impact.[13]

4. Conclusion

Drawing on a difference-in-differences model of interstate mobility following an inadvertent policy reversal in Michigan as a natural experiment, we have shown that employee non-compete agreements encourage the migration of workers from states where such contracts are enforceable to states where they are not. The result is robust to a number of placebo tests and alternative specifications. Moreover, this pattern is amplified for workers who are more collaborative and whose work is more impactful, stripping enforcing states of some of their most valuable knowledge workers.

To the extent that one can draw normative conclusions from the above findings, policymakers who sanction the use of non-competes could be inadvertently creating regional *disadvantage* as far as retention of knowledge workers is concerned. From a policymaker's perspective, the free flow of particularly high-ability talent to the best opportunities seems beneficial as long as it occurs locally (Saxenian, 1994), while such talented workers who take out-of-state jobs are a loss to the state. We believe that these findings will be of particular interest to those seeking to spur innovation and entrepreneurship locally, particularly because enticing talent from outside the state can be expensive and the prospect of (re)training local workers can be uncertain. Our findings are particularly important for policymakers because, unlike most findings regarding determinants of regional migration (Greenwood, 1997), policy regarding employee non-compete agreements is actionable. Indeed, several states including Texas, Louisiana, Florida, Idaho, New York, and New Hampshire have meaningfully altered their non-compete employment policies within the last 20 years. Moreover, Massachusetts Governor Deval Patrick announced in April 2014 his plan to seek a ban on employee non-compete agreements (Borchers, 2014). And while those immediately graduating from universities are likely not subject to a non-compete, the specter of having to submit themselves to a non-compete and possibly constrain their future career prospects within their chosen industry may induce them to leave the state.

Overall, the impact of non-compete agreements on individuals and firms still remains to be further explored in future research in order to perform a full welfare assessment. The net effect of the various advantages and disadvantages of non-competes remain unclear both theoretically and empirically. For example, from a firm's perspective, non-competes ease the challenge of retention and decrease labor costs, but they may depress R&D investment (Garmaise, 2011), and it remains unknown if they also increase the difficulty of hiring new and specialized talent. As another possible effect, individuals faced with non-competes may react in a variety of ways, such as changing their technical focus. This may be a loss for the state if inventors abandon expertise in important areas but could instead represent a net gain if changing fields engenders creativity and recombination. However, if the best inventors leave a state after they have identified promising breakthroughs, most local benefits of non-competes may be lost to states that prohibit enforcement. Finally, firms may perceive the benefits of blocking employees from moving to local competitors as greater than the risk of losing employees to out-of-state competitors and thus select away from non-enforcing state—though the concentration of high-tech firms in California's Silicon Valley is a strong counterexample. We see answering such questions as an important next step.

[13] These findings are distinct from Marx et al. (2009), which measures the ratio of internal-to-external citations as a measure of firm-specificity and also the concentration of patents within a particular technology class as a measure of specialization whereas we use the simple count of forward citations and coauthors.

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