The Evolution of U.S. Entrepreneurial and Innovation Ecosystems in Artificial Intelligence: Geographic "Pull" Factors [*]

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Abstract: What geographic pull factors shape where individuals engage in startup activity? The related literatures discuss how agglomeration forces shape the geographic locus of innovation, characterize the business environment influencing individual mobility, and suggest that local spinoffs can lead to industry clustering. To improve our understanding of why some individuals move geographies (bypassing their home social capital) to start new ventures, we evaluate three candidates: venture capital access, specialized human capital access, and co-location to access knowledge spillovers. Using startups in the artificial intelligence (AI) industry, we examine the relative empirical importance of these factors in the 2001-2018 timeframe. We find that our measures of knowledge spillover capital and human capital best explain geographic pull factors for entrepreneurship, especially after a major technological advance.

Managerial summary: Just as there is a war for talent in the workforce, there is regional competition to attract entrepreneurs and new ventures, as they can be a source of jobs and economic growth. Aside from factors documented in the literature that are under the control of public policy makers such as immigration, tax, and labor competition policy, we have less understanding of how forces under the control of managers and broader ecosystem actors can help "pull" entrepreneurs to their location. By studying entrepreneurs in the artificial intelligence (AI) industry, we find that such individuals are attracted to locations with the potential for knowledge spillover and recruiting specialized human capital. Financial capital seems to be less of a factor.

Keywords: geography of entrepreneurship; mobility; venture capital; knowledge spillovers; artificial intelligence.

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1. Introduction

Regions wish to attract startups because of their economic enhancement potential (Haltiwanger, Jarmin & Miranda, 2013); in turn, startups benefit from geographic clustering (Delgado, Porter & Stern, 2010). This positive feedback process can therefore be geographically self-reinforcing (Gambardella & Giarrantana, 2010).[1] While regions like Silicon Valley have often been discussed in the literature (e.g., Saxenian, 1994), the broader pattern of young firm mobility suggests that almost seven percent of US ventures younger than five move geographic locations, often to locations *outside* of the classic entrepreneurial hubs (Bryan & Guzman, 2023). This high rate of *firm* moves suggests that *individual* venture founders and early startup joiner mobility may be even more significant (individuals likely anticipate their ecosystem preferences and needs). While achieving startup liquidity (going public or being acquired) is a recognized "push" factor loosening individuals' organizational bonds with their current employer (Stuart & Sorenson, 2003a), we know less about the "pull" factors attracting individuals to destination geographies.

We therefore pose the research question: what geographic pull factors shape where individuals engage in startup activity? We examine three candidate geographic factors: financial capital, specialized human capital, and co-locating with knowledge sources to capture knowledge spillovers. Each of these geographic pull factors has been individually discussed as attracting entrepreneurs in the literature. Financial capital, via the venture capital (VC) industry for entrepreneurial funding, has been characterized as local in nature due to the monitoring and value-added role of such investors in the face of potential information asymmetries (e.g., Bernstein, Giroud & Townsend, 2016). Specialized human capital is a classic economic agglomeration force

[1] For example, over 40 angel investors who made their fortunes in Google's initial public offering seeded over 200 new ventures in Silicon Valley, thereby recycling both financial capital and know-how in the region. (John Tozzi, "Google's Angels," *Bloomberg BusinessWeek*, Feb. 26, 2010).

due to lower costs of reallocating talent to the most productive use, which in turn leads to employer clustering as well. Finally, accessing knowledge spillovers is facilitated by local (social) interactions (Jaffe, Trajtenberg & Henderson, 1993; Zucker, Darby & Brewer, 1998). Because there is little *comparative* theory prioritizing these pull factors, especially in knowledge-intensive settings, and the fact that any individual mobility must overcome well-understood geographic inertial factors in home geographies (Dahl & Sorenson, 2012; Buenstorf & Klepper (2009), we refrain from formulating specific predictions ahead of our empirical inquiry.

We utilize the empirical context of the US artificial intelligence (AI) industry over the 2001 to 2018 timeframe. This longitudinal window is salient, as it allows us to observe modern-day AI emergence and spans key advances in the industry such as neural networks and deep learning. AI is also more representative of the modern knowledge-based economy compared to prior empirical settings such as the manufacturing industry, where the economics of agglomeration literature has predominantly been based (e.g., Ellison, Glaeser & Kerr, 2010). Within this setting, we conduct our analysis at the inventor-year-potential metropolitan statistical area (MSA) level. We use patent data to track (inferred) inventor mobility patterns, with the outcome of interest moving to a startup in a different MSA. This framework allows us to explore the micro-foundational nature of the pull factors from the individual perspective in shaping their strategic decision regarding founding or joining her venture in a particular geography over alternatives. We find destination environments with higher levels of knowledge spillovers and computer science workers, but not venture capital (VC) funds, receive more entrepreneurial migration.

2. Literature and Theory

Two strands of literature are especially relevant to our research question. A literature on individual mobility and a subset of that literature, on spinoffs and employee entrepreneurship, serves as important background, particularly to individual "push" factors from a home location. A second stream, related to clustering of industrial activity, serves as background to our theorizing about potential geographic "pull" factors attracting talent to a destination location.

2.1 Individual mobility, spinoffs, and geographic "push" factors

There is widespread recognition in the literature that individuals are the carriers of specialized knowledge, and that industry evolution typically proceeds via spinoffs and employee entrepreneurship, the phenomenon of individuals leaving (typically incumbent) organizations to found or join a new venture (e.g., Buenstorf & Klepper, 2009; Sørensen & Fassiotto, 2011). This stream of literature is sizeable, and there are multiple views within it of the proximate cause of spinoffs, including disagreements, learning, knowledge under-utilization and more (see Kaul, Ganco & Raffiee, 2024 for a recent example and literature review). Notably, however, this literature lacks strong geographic implications. Largely left unexplained is the distant location of individuals and spinoffs outside of the focal parents' clusters. An exception is Berchicci, King & Tucci (2011), who find evidence that spinoffs with more aggressive strategies tend to remain proximate to the parents to leverage pre-existing relationships.

Distant geographic moves need to overcome individual inertial forces. Studies examining different geographic samples conclude that there is a home bias in entrepreneurial location (Michelacci & Silva, 2007; Dahl & Sorenson, 2010), presumably because of accumulated and embedded social relations, which can be both organizational- (e.g., accessing suppliers and customers) as well as personal-resources (friends and family). Should those factors be overcome, several studies have examined a variety of (public) policies which can be regarded as "push" factors in aiding individual mobility: more accommodating immigration policies (Lee & Glennon, 2023), lower tax policies (Bryan & Guzman, 2023), and not enforcing covenants not to compete

(Marx, Strumsky & Fleming, 2009). We have less knowledge of managerial levers which shift entrepreneurs *out* of their home locations, aside from the general understanding that entrepreneurial public offerings or acquisitions are salient organizational events which loosen the individual employment bond with their parent organizations (Stuart & Sorenson, 2003a).

2.2 Industry agglomeration and geographic "pull" factors

A dominant perspective on the geography of industrial activity is due to Marshall (1920). He pointed to three drivers of industry clustering, or agglomeration: minimizing costs of transport (intermediate and final goods), labor (via labor market pooling), and accessing ideas (knowledge spillovers in modern parlance). While a full review of the geography of innovation literature is beyond our scope, the influence of Marshallian agglomeration economics is substantial (e.g., Shaver & Flyer (2000), who find that clustering is a more significant force for smaller rather than larger firms). We discuss two Marshallian forces, specialized labor and knowledge spillovers, as geographic pull factors which could be especially relevant in digital service industries, such as the one we empirically examine, along with a third, entrepreneurial financial capital, which the literature suggests is important for vibrant entrepreneurial ecosystems (Gompers & Lerner, 2001).

Specialized labor is a key Marshallian agglomerating force because such individuals want to hedge against firm-specific shocks which might either displace them or allow them to find the most productive use of their skills by locating where a pool of firms can compete for their talent. Firms and their founders also want to locate in areas with access to specialized skills they demand, which results in industry agglomeration. Though not within the domain of entrepreneurship, Fallick, Fleischman & Rebitzer (2006) find empirical evidence of individual mobility in the Silicon Valley computer industry consistent with this Marshallian agglomeration force.

Marshall (1920) also discussed firm clustering due to capturing knowledge spillovers. Larger-scale empirical support arrived decades later (Jaffe, Trajtenberg & Henderson, 1993) with evidence consistent with the notion that knowledge flows (proxied by patent citations) are a local, likely social, process even after controlling for the existing geography of production (Audretsch & Feldman, 1996). Zucker, Darby & Armstrong (2002) found that biotechnology venture founding locations were often co-located with scientific stars at the birth of that industry. Gambardella & Giarrantana (2010) find that localized knowledge spillovers become a positive self-reinforcing cycle with knowledge workers gaining higher productivity. Owen-Smith & Powell (2004) show that geographic propinquity and organizational form link spillovers to increased innovation.

The relationship between *entrepreneurship* and knowledge spillovers is somewhat less understood, however.[2] In theorizing about the relationship, Agarwal, Audretsch & Sarkar (2007) conceptualize an alternative process of "creative construction" which links knowledge spillover to strategic entrepreneurship. Incumbents make knowledge investments through individuals, who exploit this knowledge to form new ventures. Knowledge spillovers can be of different types: tacit or codified, technical or non-technical. Chatterji (2009) finds that in medical devices, non-technical (tacit) spillovers such as regulatory know-how drives performance in spawned ventures.[3]

Finally, while not a traditional Marshallian agglomeration force, venture capital (VC) funding has been characterized as local because of the active nature of early-stage investments, often requiring close monitoring and even participating in startup corporate governance (Bernstein

[2] Meanwhile, there have been advances about knowledge flows as an agglomerating force. Davis and Dingel (2019) posit that idea exchange is linked with creating spatial knowledge economies as compared to the more traditional Marshallian factors involving physical goods.

[3] While prior literature has theorized about geographic ramifications to entrepreneurship that is borne out of spillovers (Audretsch & Lehmann, 2017), empirical support is limited. Additionally, extant research is focused on specific regions (such as Silicon Valley) with limited appreciation for geo-spatial heterogeneity, which poses questions about generalizability. In fact, Almeida & Kogut (1999) show that knowledge localization may be region-specific with significant variation in the degree of localization across geographies.

et al., 2016). In addition, the information fidelity is best in short ranges, which is important in the VC funding context. Sorenson & Stuart (2001) find evidence consistent with these ideas.

3. Data, Variables, and Empirical Specifications

Our analysis is based on the career trajectories of 180,138 distinct individual inventors who filed at least one AI patent by the year 2019 as identified by the Artificial Intelligence Patent Dataset (AIPD) developed by the United States Patent & Trademark Office (USPTO).[4] To measure inventor mobility, we follow existing literature (e.g., Marx et al. 2009; Melero et al., 2020) in identifying an inventor (from the USPTO PatentsView database) as having changed her employer if she files two successive patent applications that are assigned to different firms. Upon change of employers, we track if an inventor departs from her current MSA location and moves into one of the top MSA destinations (defined as the top 26 MSAs that account for 70% of inflows of AI inventors in our sample period from 2001 to 2018) for AI inventors.[5] Each combination of inventor-employer-year corresponds to 26 observations with each observation evaluating whether the focal inventor moves into one of the top MSAs between two successive patents (using midpoint years). As a result, the unit of analysis is at the (three way) inventor-employer, potential destination MSA, and year level. In total, our sample contains 21,881,653 observations associated with cross-MSA mobility of 180,138 inventors between 9,853 home-destination MSA dyads.

Our outcome of interest is an inventor changing her employer and moving to a startup (defined as entities with no more than five years of history since its first patent application) in the potential destination MSA between two successive patent applications.[6] Our main empirical

[4] The AIPD identifies patents that involve AI component technologies among all the patents filed to USPTO, based on a machine learning approach developed by the USPTO. Giczy et al. (2022) provides a detailed description of construction methods and structure of the dataset.
[5] The results are robust to designating the top 48 MSAs, which correspond to 80% of the MSA destinations, but the estimation is far more computationally intensive.
[6] Figure 1 (Panel A) shows that about 27% of inventors move between two successive patents, with the majority of those movers moving within their home MSA. About 6% of inventors move to a top-26 destination MSA. Among the

analysis investigates how focal destination "pull" factors affect subsequent inventor mobility into a startup, and our main specifications are estimated via conditional (fixed effects) logit, given the discrete nature of our outcome variable, with panels identified by the individual inventors, and fixed effects for origin MSA, destination MSA, and year.[7] Our robustness specifications include multinomial logit (recognizing individuals' menu of choices rather than discrete choice) and simultaneous equation estimation (recognizing potentially endogenous individual moves). In the conditional and multinomial logits, only observations with variation in outcomes are employed.

Our independent variables proxy for the three potential destination MSA pull factors we theorized relating to individual moves: financial capital, human capital and knowledge spillover capital. In constructing those variables, we consider a three-year time window prior to the focal year of an observation in which we difference our pull factor measures associated with the destination from the origin MSA. For financial capital, we use data from Pitchbook (supplemented with VentureXpert and Crunchbase in the pre-2007 era) to measure the number of VC funds newly raised by VC firms located in an MSA in the three-year time window preceding the year of interest. To measure the human capital pull factor, we use data on computer science occupation employment from the Occupational Employment and Wage Statistics (OEWS) program by the US Bureau of Labor Statistics, aggregated to the occupation-MSA-year level (differenced counts between the destination and home MSAs over the prior three-year period). Finally, to quantify knowledge spillovers from one MSA to a focal inventor, we use patent citations as suggested by the literature (Jaffe et al., 1993). For each potential destination MSA for a given inventor-year, we count

movers to a top-26 destination MSA, Panel B of the same figure shows that most of the movers are to an established firm (with the rate increasing over the time frame we study).

[7] All other outcomes – an inventor remaining in her home MSA, moving to an MSA other than the focal destination, or moving to an incumbent firm – take an outcome of zero, and in this specification, all observations associated with an individual inventor would be dropped if the inventor did not move to a startup in any of the potential destination MSAs in consideration.

citations made by an inventor to patents filed by inventors located in a potential destination MSA in the three-year window preceding the year of interest.

We also construct a variety of control variables that might affect inventor mobility outside of our focal pull factors. First, we control for pre-existing MSA-level differences in knowledge environments as measured by *differences* in AI patents (using the AIPD) and AI-area scientific publications (as recorded in Microsoft Academic Graph (MAG), a database of scientific publication and citation relationships). As ventures may also locate to be closer to potential acquirers, we use the SDC database on acquisitions to construct our measure. For each MSA dyad, we count the number of acquisitions with a target acquiree AI firm located in a home MSA and an acquiring firm located in the destination MSA in a three-year time window prior to a year of interest.[8] At the employer (assignee) level, we also control for whether an assignee has been a target acquiree in an acquisition deal. As the literature suggests that employer age may systematically relate to spawning patterns (Gompers et al. 2005), we also construct a proxy for the inventor's employer age (years since the first patent applied for by the employer-assignee to date).

Second, we control for economic condition differences between the potential destination and home MSAs. *Unemployment (diff)* measures the differences in the unemployment rates in the potential destination and home MSAs in the year prior to the year of interest. Using the housing price index time-series extracted from the US Federal Reserve Economic Data (FRED), we calculate *Housing Price Index (diff)*, the housing price growth rate difference between the destination and the home MSAs in a three-year time window prior to the year of interest.

[8] A firm is identified as AI-focused if one or more of the following conditions is true: (i) a firm is assigned at least one AI patent based on the AIPD records; (ii) a firm is in the AI field according to the Crunchbase classification; (iii) at least one AI keyword appears in the descriptions or keywords of firms covered by Crunchbase or Pitchbook (we use AI keywords identified by Lou & Wu (2021)). We find 2,787 domestic acquisitions of AI focused acquiree firms located in the US from 1990 to 2018 and aggregate the data to the MSA-dyad-year level with a target acquiree located in a home MSA and an acquiring firm located in the destination MSA.

A final set of controls proxy for inertial forces. As a proxy for the social capital and embeddedness of an inventor in her current residing MSA location, we count the total number of patents filed by a focal inventor in the location up to the year of the observation. We also count the number of AI-focused firms founded in a potential destination MSA since 1998 to the year of interest as a control for agglomeration forces. Table 1 reports the summary statistics.

4. Results

Table 2 presents conditional logit estimates (expressed as odds ratios) of how different pull factors relate to AI inventor mobility across MSAs. Columns 1 through 4 report results using *Move to a startup in the focal MSA* as the dependent variable while Column 5 presents a comparison outcome variable (=1) if an inventor moves to an *incumbent firm* in the focal MSA for her next patent and zero otherwise. The control variable effects are in line with existing literature: there are significant home location inertial forces (proxied by inventors with more patent applications in her current residing MSA). Also, more AI patents in the potential destination MSA relative to the home MSA are associated with inventor mobility to that destination MSA. The same pattern holds for recent destination acquisition activity. We also find that companies with longer operations are more likely to spawn founders, as suggested by the significant odds ratio of the *age of current assignee firm* variable that is greater than one, consistent with Gompers et al. (2005).

Turning to the main results on MSA pull factors, we find that our measures of knowledge spillovers and specialized human capital (but not VC supply) are positive and statistically significant correlates of inventors moving into a new MSA and founding or joining a new venture. The estimated effect magnitudes suggest that doubling an inventor's citations to patents filed in a focal MSA is associated with about a 23% increase in the likelihood of moving to a startup in a focal MSA.[9] For specialized human capital, as the computer science employment level in the focal destination MSA increases by 100,000, the likelihood of an individual inventor moving to a startup in the focal MSA increases by 7.6%.[10] In comparison, regarding the move to an incumbent in a focal MSA, while knowledge spillovers are a significant pull factor associated with inventors' moving into an incumbent firm across MSA, neither specialized human capital nor VC funding supply are significant. These results are robust to excluding the two Silicon Valley MSAs as potential destinations, suggesting the overall effect is not localized to that region.

While the above estimates reflect average effects over the entire 2001-2018 time span, we also know that factor markets (including labor markets) and technologies adjust over time (due to, for example, developments in low-code programming environments commoditized certain skills). Moreover, the prior literature has documented that while geographic proximity to capture knowledge spillovers is important at the birth of an industry, as knowledge becomes codified, such co-location for entrepreneurial starts is less important (Zucker, et al., 1998). An important advance in the AI industry was developing a convolutional neural network (dubbed "AlexNet") in 2012. This technology significantly improved image recognition, and is widely considered a key advance (*The Economist*, June 25, 2016). We examine how this advance may have shifted the salience of the geographic pull factors we previously examined. Table 3 reports the results (odds ratios of conditional logits) of introducing interaction terms between *Post AlexNet* (an indicator for the post-2012 period) and each of the pull factor variables into the baseline specification. While knowledge

[9] Expressed in a different way, a doubling of inventors' citations to patents filed in a focal MSA is associated with an additional 15,999 inventors moving into startups in that focal MSA. Since there are 68,666 distinct inventor-assignee-years in the sample, the aggregate number of migrant-inventors is given by: $23.3\% \times 68{,}666 \approx 15{,}999$.
[10] This translates to 5,219 additional inventors moving to a startup in the focal MSA ($7.6\% \times 68{,}666 \approx 5{,}219$).

spillovers are slightly lower after AlexNet, human capital (computer scientists) is a significant startup pull effect only in the post-AlexNet period. VC supply has a small effect throughout.[11]

We conduct two robustness checks. The first is to empirical specification (multinomial- rather than conditional-logit). Table 4 reports multinomial logit relative risk ratios. The baseline outcome corresponds to the case that an inventor stays in her home MSA or moves to an MSA different from the top MSAs in consideration (our results are robust to excluding inventors that move to a non-top MSA). Two outcomes are possible: moving to a startup or an established firm in the focal MSA.[12] The statistical and economic results are largely in line with those reported in our baseline Table 2. The second check seeks to understand if the main results are overturned when we employ an empirical strategy to address endogenous (or unobserved) cross-MSA individual moves via a simultaneous equation model. The equations predict two events: (i) an inventor moves into a focal destination MSA from her original MSA; (ii) an inventor becomes affiliated with a startup in a focal destination MSA. The main idea is that inventor mobility is shaped, in part, by exogenous staggered regime changes in non-compete clause enforceability. We adopt the measures developed by Ewens & Marx (2017) and use them as instrumental variables.[13] The results are reported in Table 5 and confirm our baseline effects.[14]

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[11] Comparing these results to individual mobility into established firms (Column 5), the only significant pull factor is knowledge spillovers, which also decline in economic importance in the post-AlexNet period.

[12] The large number of fixed effects (8,491 inventors and 8,008 MSA-dyads) pose challenges to estimating the multinomial model. Therefore, we only include year fixed effects and destination MSA fixed effects in this estimation.

[13] Simultaneously estimating a two-equation system of linear models allows for correlated error terms (the positive statistical test presented at the bottom of Table 5 suggests such a correlation). We employ the maximum simulated likelihood method using the GHK simulator and make use of the user-written command "cmp" in Stata. We only include year and destination fixed effects due to model convergence challenges once fixed effects for home MSAs and inventors are included.

[14] Since knowledge spillovers are measured by patent citations which in turn can arise from inventor or patent-examiner imposed citations (Alcacer & Gittelman, 2006), we also check if the main results persist if we only include the (exogenously-imposed) examiner citations. This helps mitigate the potential selection effect of an inventor-citation based measure of knowledge spillovers. We find (unreported regressions, but available on request) evidence of robustness. In a specification including both forms of citation-based knowledge spillovers, examiner-imposed citations are over four times larger in economic magnitude compared to that of inventor-included cites (both groups are statistically significant).

5. Discussion and Conclusion

By examining individual-level talent (inventor) mobility across metropolitan areas, we provide an analysis of entrepreneurial geographic pull factors within the artificial intelligence sector, an exemplar of the knowledge economy. In doing so, our aim is to contribute to the nascent geography of entrepreneurship literature. While the prior literature has primarily focused on public levers for attracting entrepreneurial firms, such as immigration or tax policy, our work complements that perspective by examining broader business environment conditions which attract entrepreneurs to a location. Our results are consistent with the proposition that entrepreneurs seek access to both specialized talent and knowledge, though future work which explores heterogeneity in knowledge spillover environments for entrepreneurship is a high priority.

Financial capital, in our context, is not a significant pull factor for AI entrepreneurs. This finding is consistent with the results of Marx & Hsu (2022) that local VC supply is not a good predictor of entrepreneurial commercialization of science (even when controlling for the technical advance). However, it may be the case that accessing experienced VC may be important for entrepreneurial *performance*, as consistently shown in the literature (e.g., Bernstein, et al. 2016 and references therein). As such, evaluating the performance of such individual moves (especially moves which may be exogenously-driven) represents fertile ground for future research. Indeed, Stuart & Sorenson (2003b) find that the local forces which attract biotechnology entrepreneurs to a location are not the same as those which correlate to venture performance.

We acknowledge limitations of our work which will hopefully be addressed in future work: identifying individual moves using patent data (and the related potential selection effects) as well as the associational rather than causal interpretation of our results. Nevertheless, we hope this effort spurs further development in the literature on the micro-foundations of entrepreneurial geography.

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Table 1. Summary statistics

Sample observations are at the inventor-employer-destination MSA (potential)-and-year level. The sample contains individual inventors that filed at least two patents from 2001 to 2018, and at least one of their filed patents are AI patents. This table reports summary statistics of the sample used in the baseline analysis (i.e., conditional logit estimation) that includes 8,491 distinct inventors with variation in the dependent variables (i.e., move to a startup/an established firm in a top MSA). The top 26 destination of MSAs are considered that account for inflows of 70% of cross-MSA migrants in the sample.

	Mean	p50	Min	Max	SD
=1, move to a top MSA	0.009	0.000	0.000	1.000	0.094
=1, move to a startup in a top MSA	0.005	0.000	0.000	1.000	0.073
=1, move to an est. firm in a top MSA	0.004	0.000	0.000	1.000	0.059
Log(Inventor's citations to patents filed in a focal top MSA)	0.017	0.000	0.000	8.363	0.194
Diff in no. of newly raised VC funds (dest.-home)	-43.033	-12.000	-494.000	494.000	129.051
Diff in employment in CS (dest.-home, in 100,000)	-0.232	-0.287	-8.612	8.812	2.419
Log(No. of patents filed by an inventor in the home MSA)	1.517	1.099	0.693	7.480	1.023
Whether current assignee is acquired	0.159	0.000	0.000	1.000	0.366
Log(M&A deals for dest. MSA- home MSA)	0.342	0.000	0.000	3.296	0.587
Log(Age of current assignee firm)	2.359	2.485	0.000	6.846	1.045
Log(no. of startups formed in the dest. MSA)	4.739	4.682	1.386	7.818	1.156
Diff in patent no. (in thousands)	-2.137	-0.757	-18.944	19.009	5.976
Diff in pub. no. (in thousands)	1.936	0.304	-24.976	42.398	10.570
Diff in unemployment rates	-0.096	-0.000	-18.400	10.100	1.558
Diff in housing price growth rates	-0.020	-0.019	-0.926	0.799	0.190
Observations	1,865,428				

Figure 1. Patterns of inventor moves over time

These figures illustrate move of AI inventors between two successive patents over time. Panel A plots the fractions of AI inventors that move within their home MSA, move to one of the top MSAs, and move to an MSA different from the top MSAs, respectively. The top 26 destination of MSAs take in the highest number of migrant-inventors in the sample period and jointly account for 70% of cross-MSA migrants. Panel B zooms in inventors that move into one of the top MSAs.

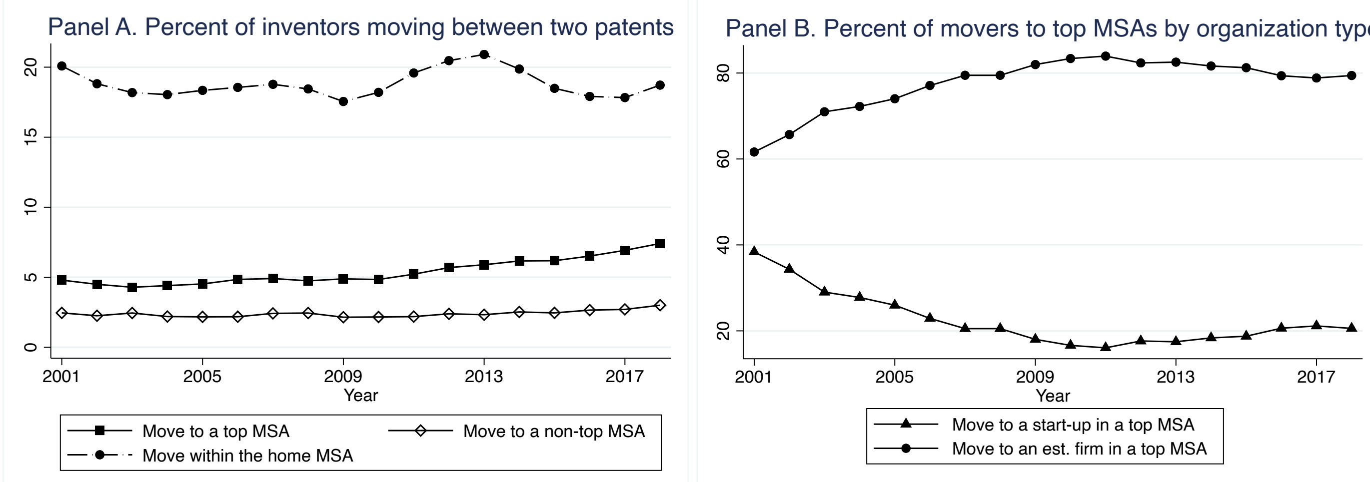

Table 2. Effects of differences in the pull factors on moving

This table presents **odds ratio** from fixed effect logistic regression that is conditional on individual inventors. Sample observations are at the inventor-year-(potential) destination MSA level. The estimation considers inventor observations with variation in the dependent variable (i.e., moving to a start-up/an established firm in a top MSA) from 2001 to 2018. See Section 3 for an explanation of the controls included in the estimation. Standard errors in parentheses are clustered at the individual inventor level. * $p < .1$, ** $p < .05$, *** $p < .01$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	DV: Move to a startup in a focal MSA				**DV: Move to an est. firm in focal MSA**
Log(Inventor's citations to patents filed in a focal top MSA)	1.239*** (0.0516)			1.233*** (0.0517)	1.287*** (0.0627)
Diff in no. of newly raised VC funds (dest.-home)		1.000 (0.000179)		1.000 (0.000194)	1.000 (0.000230)
Diff in employment in CS (dest.-home)			1.073** (0.0344)	1.076** (0.0371)	1.003 (0.0413)
Log(No. of patents filed by an inventor in the home MSA)	0.571*** (0.0161)	0.572*** (0.0161)	0.573*** (0.0163)	0.573*** (0.0163)	0.712*** (0.0148)
Log(M&A deals for dest. MSA-home MSA)	1.509*** (0.0344)	1.510*** (0.0345)	1.502*** (0.0343)	1.501*** (0.0343)	1.415*** (0.0463)
Log(Age of current assignee firm)	2.298*** (0.0482)	2.297*** (0.0482)	2.297*** (0.0484)	2.299*** (0.0484)	0.774*** (0.0101)
Log(no. of startups formed in the dest. MSA)	1.031 (0.109)	1.023 (0.110)	1.032 (0.111)	1.038 (0.114)	1.013 (0.152)
Diff in patent no. (dest.-home)	1.036*** (0.00588)	1.035*** (0.00601)	1.032*** (0.00614)	1.032*** (0.00619)	1.002 (0.00680)
Diff in pub. no. (dest.-home)	0.996 (0.00332)	0.997 (0.00352)	0.994* (0.00348)	0.994 (0.00383)	1.003 (0.00540)
Year fixed effect	Y	Y	Y	Y	Y
Home MSA fixed effect	Y	Y	Y	Y	Y
Pot. Dest MSA fixed effect	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y
Observations	1,865,428	1,865,428	1,865,428	1,865,428	1,021,007
Pseudo R^2	0.15	0.15	0.15	0.16	0.11

Table 3. Post AlexNet (year 2012) effects of differences in the pull factors on moving

This table presents **odds ratio** from fixed effect logistic regression that is conditional on individual inventors. Sample observations are at the inventor-year-(potential) destination MSA level. The estimation considers inventor observations with variation in the dependent variable (i.e., moving to a start-up/an established firm in a top MSA) from 2001 to 2018. See Section 3 for an explanation of the controls included in the estimation. *Post AlexNet* equals to one for all observations after year 2012. For all the interaction terms with *Post AlexNet*, the **net effects** of the pull factor in question are reported. Standard errors in parentheses are clustered at the individual inventor level. * $p < .1$, ** $p < .05$, *** $p < .01$

	(1)	(2)	(3)	(4)	(5)
	DV: Move to a startup in a focal MSA				**DV: Move to an est. firm in focal MSA**
Log(Inventor's citations to patents filed in a focal top MSA)	1.267***			1.254***	1.327***
	(0.0756)			(0.0765)	(0.0812)
−Post AlexNet	1.213***			1.210***	1.240***
	(0.0651)			(0.0650)	(0.0781)
Diff in no. of newly raised VC funds		0.999***		0.999***	1.000
		(0.000249)		(0.000264)	(0.000336)
−Post AlexNet		1.000*		1.000	1.000
		(0.000187)		(0.000200)	(0.000232)
Diff in employment in CS (dest.-home)			1.041	1.053	1.037
			(0.0346)	(0.0373)	(0.0442)
−Post AlexNet			1.079***	1.080**	1.003
			(0.0347)	(0.0371)	(0.0414)
Post AlexNet	2.152***	4.181***	2.586***	4.344***	3.999***
	(0.577)	(1.231)	(0.726)	(1.322)	(1.575)
Controls	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y
Inventor fixed effect	Y	Y	Y	Y	Y
Home MSA fixed effect	Y	Y	Y	Y	Y
Pot. Dest MSA fixed effect	Y	Y	Y	Y	Y
Observations	1,865,428	1,865,428	1,865,428	1,865,428	1,021,007
Pseudo R^2	0.15	0.15	0.15	0.16	0.11

Table 4. Results from multinomial logit estimation

This table presents **relative risk ratios** from multinomial logit estimation. Sample observations are at the inventor-year-(potential) destination MSA level. The estimation considers inventor observations with variation in the dependent variable (i.e., moving to a top MSA) from 2001 to 2018. In the baseline outcome, a focal inventor does not move. Column 1 presents the relative risk ratios of *moving to a startup in a focal MSA* while Column 2 presents results associated with the outcome of *moving to an est. firm in a focal MSA*. See Section 3 for an explanation of all the controls included in the estimation. Standard errors in parentheses are clustered at the individual inventor level. * $p < .1$, ** $p < .05$, *** $p < .01$

	(1) **Outcome 1: Move to a startup in a focal MSA**	**(2)** **Outcome 2: Move to an est. firm in a focal MSA**
Log(Inventor's citations to patents filed in a focal top MSA)	1.214^{***}	1.382^{***}
	(0.0452)	(0.0284)
Diff in no. of newly raised VC funds	1.000^{**}	1.001^{***}
	(0.000114)	(0.0000612)
Diff in employment in CS (dest.-home)	1.027^{***}	1.012^{**}
	(0.0103)	(0.00535)
Log(No. of patents filed by an inventor in the home MSA)	0.657^{***}	0.731^{***}
	(0.0103)	(0.00614)
Whether the current assignee is acquired	1.119^{***}	1.130^{***}
	(0.0285)	(0.0140)
Log(No. of acq. deals w. acquirors in the dest. MSA)	1.309^{***}	1.269^{***}
	(0.0255)	(0.0139)
Log(Age of current assignee firm)	1.041^{***}	1.167^{***}
	(0.0116)	(0.00650)
Diff in patent no. (dest.-home)	1.022^{***}	1.011^{***}
	(0.00272)	(0.00140)
Diff in pub. no. (dest.-home)	1.004	1.010^{***}
	(0.00250)	(0.00143)
Other controls	Y	Y
Pot. Dest. MSA fixed effect	Y	Y
Year fixed effect	Y	Y
Observations	6,000,953	
Pseudo R^2	0.09	

Table 5. Simultaneous equation estimation results (correcting for moving selection)

This table presents results from estimating a system of linear equations that consider moving into a focal MSA and moving to a startup in a focal MSA simultaneously, as explained in Section 3. For legibility, the dependent variable is scaled by 100. The estimation considers observations of all the inventors who have filed at least two patents (at least one of their filed patents being AI patents), regardless of whether they migrated across MSAs in the sample period. See Section 3 for an explanation of the controls included in the estimation. Standard errors in parentheses are clustered at the individual investor level. * $p < .1$, ** $p < .05$, *** $p < .01$

	(1) **DV: =1, move to a focal MSA**	**(2)** **DV: Move to a startup in a focal MSA**
Non-compete law change (home MSA)	0.00578** (0.00270)	
Non-compete law change (dest. MSA)	-0.00809*** (0.00233)	
Log(Inventor's citations to patents filed in a focal top MSA)	0.149*** (0.0135)	0.0147*** (0.00450)
Diff in no. of newly raised VC funds	0.000111*** (0.0000138)	0.0000358*** (0.00000706)
Diff in employment in CS (dest.-home)	0.00150 (0.00105)	0.000875* (0.000462)
Controls	Y	Y
Pot. Dest MSA fixed effect	Y	Y
Year fixed effects	Y	Y
atanh $(\rho(\epsilon, \zeta))$	0.494*** (0.00287)	
Prob>χ^2	0.000	
Observations	21,881,653	